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Yonca Erdebil
AUTEUR DE LA THÈSE / AUTHOR OF THESIS

M.A.Sc. (Electrical Engineering)
GRADE / DEGREE

School of Information Technology and Engineering
FACULTÉ, ÉCOLE, DÉPARTEMENT / FACULTY, SCHOOL, DEPARTMENT

Modeling Severe ATV Injuries Using Artificial Neural Networks

TITRE DE LA THÈSE / TITLE OF THESIS

M. Frize
DIRECTEUR (DIRECTRICE) DE LA THÈSE / THESIS SUPERVISOR

CO-DIRECTEUR (CO-DIRECTRICE) DE LA THÈSE / THESIS CO-SUPERVISOR

EXAMINATEURS (EXAMINATRICES) DE LA THÈSE / THESIS EXAMINERS

A. Chan

A. El Saddik

Gary W. Slater
LE DOYEN DE LA FACULTÉ DES ÉTUDES SUPÉRIEURES ET POSTDOCTORALES /
DEAN OF THE FACULTY OF GRADUATE AND POSTDOCORAL STUDIES

Modeling Severe ATV Injuries Using Artificial Neural Networks

By

Yonca Erdebil,

B.Sc., Electrical Engineering, Queen's University

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Abstract

This thesis develops a model for severe all-terrain vehicle (ATV) injuries using artificial neural networks (ANNs) with data from the Canadian Hospitals Injury Reporting and Prevention Program (CHIRPP) and analyzes the model to find the contribution of each factor in predicting severe injury. From the analysis of the model, recommendations are made on the factors that should be investigated further to reduce severe injuries.

An analysis of ANN architecture shows that a configuration with no hidden nodes or layers results in optimal performance. The performance results of the ANN gives a logarithmic-sensitivity index of 0.09, sensitivity of 44%, specificity of 84%, correct classification rate (CCR) of 70% and receiver operating curve (ROC) area of 0.72. The most important input factors for predicting severe injury are: nature of injury, helmet, age group, mechanism, seat position, circumstances of collapse, body part and sex.

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Acronyms and Symbols

λ, lambda	weight-elimination constant
α, mmtm	momentum
ANN	artificial neural network
ASE	average squared error
ATV	all-terrain vehicle
CCR	correct classification rate
CHIRPP	Canadian hospitals injury reporting and prevention program
CP	constant predictor
err_ratio	error ratio
lambda_inc	lambda increment, i.e. weight elimination constant increment
lambda_dec	lambda decrement, i.e. weight elimination constant decrement
LCDC	Laboratory Centre for Disease Control
lr	learn rate
lr_inc	learn rate increment
lr_dec	learn rate decrement
MIRG	Medical Information-technology Research Group, (University of Ottawa and Carleton University)
ROC	receiver operating curve
w_0	weight-elimination scale

1 Introduction

When thinking of health problems, cancer and AIDS may come to mind immediately; however, the number one cause of death for individuals under the age of 20 is actually injury. In 1992, 1452 Canadians under the age of 20 died from injury related causes, whereas there were 310 deaths from cancer and 113 deaths from infectious diseases. Furthermore, injury was the cause of about 1 in 6 hospitalizations for pathological reasons for the same age group [1].

Injury prevention begins with finding injury trends or new types of injuries. Over the past decade, the number of all-terrain vehicle (ATV) injury deaths has steadily been climbing. An all-terrain vehicle is a small three or four-wheeled motorized buggy made to be driven off public roads (i.e. off-road). Another name for a three-wheeled ATV is an all-terrain cycle or ATC and a four-wheeled ATV is also called a quad bike or simply a quad. There are six and eight-wheeled ATVs but these types of ATVs are not as common.

Ideally, we should learn from our mistakes by using past injury information to aid in preventing future injuries. Health Canada's Canadian Hospitals Injury Reporting and Prevention Program (CHIRPP) has collected and analyzed injury information. Although Statistics Canada collects data concerning mortality and hospitalization, CHIRPP provides detailed injury information for emergency room visits. This data can be used to establish injury prevention initiatives, to assess the effectiveness of injury prevention programs and to find injury trends.

CHIRPP has a large amount of data that requires a great amount of processing resources to analyze. One tool that can be used to model this data is called an artificial neural network (ANN). An ANN's functionality is analogous to the brain and features the ability to accept many input variables at once, process them in parallel and produce an outcome. It is commonly used to solve complex problems such as pattern recognition. ANNs can model complex systems and solve some tasks faster than many implementations on a personal computer [2]. They also require little data pre-processing unlike many statistical modeling techniques.

This analysis focuses on injuries caused by all-terrain vehicles (ATVs) and uses information about the circumstances surrounding the injury. The ANN is designed to predict whether particular ATV circumstances will result in a severe or non-severe outcome based on these ATV injury circumstances. As the feed-forward ANN is trained and optimized by a back-propagation learning algorithm, certain circumstances are excluded, as they appear to be irrelevant for predictability. The result is a model for determining ATV accident severity and possible contributing factors to severe injury.

1.1 Thesis Statement and Objectives

The objective of this thesis is to use artificial neural networks to determine the factors that are central in predicting the severity of an ATV injury. In so doing, the suitability of ANNS in generating information for injury prevention programs is demonstrated. Based on the results of the analysis, recommendations are made on which factors should be investigated further.

A study of ATV injuries was selected based on the observation that there are an increasing number of ATV injuries and the severity is higher than most other forms of injury. In fact, over

36% of ATV injuries are severe injuries [1]. An analysis of ATV injury factors could assist injury-prevention groups and ATV manufacturers in creating safer vehicles and recreational practices.

The main motivation behind this work is to find the factors that play a significant role in predicting ATV injury severity so that these factors can be used by educators and injury prevention programs to reduce the number of future ATV injuries. An ANN is ideal for achieving these goals because it can accommodate all the injury data simultaneously without initial biasing of the factors.

The first step in carrying out the proposed work is to format the CHIRPP database, obtained from Health Canada's Injury and Child Maltreatment Section in the Health Surveillance and Epidemiology Division, in a way that can be handled by the ANN for the above purpose. Consequently, transforming the raw database into something better suited for analysis required extensive study and many consultations with Health Canada.

Second, the ANN must be trained and optimized to predict if a particular ATV injury results in a severe injury. This requires significant reprogramming of the ANN. The synaptic weights of the ANN are extracted and assessed to find the factors that are fundamental in predicting injury severity. In addition, a basic statistical analysis, including correlation and frequency analysis, is carried out to sustain the ANN results.

Finally, conclusions are drawn and recommendations are made on how to further apply the CHIRPP database to improve health care and injury prevention programs.

1.2 Thesis Outline

This section provides a brief outline of the subject matter within each chapter.

Chapter 2 provides background information on the issues and concepts dealt with in this thesis. This includes a description of the injury database, what data the ANN uses, and a review of ATV technology. Lastly, there is a preliminary analysis given of the injury data prevalence and profile.

Chapter 3 introduces the main issues of data selection, data modeling techniques and ANN analysis. The ANN analysis section of Chapter 4 describes ANN architectures, learning algorithms, and outlines the optimization techniques used to achieve efficient and accurate models. The following section gives a review of another application of ANNs in the health care environment and previous modeling done with the injury database.

Chapter 4 outlines the problem and methodology. First, there is an explanation of how the ATV data ARE organized once it is extracted from the main injury database. ANN algorithms are then described, as well as the ANN performance measures, implementation, stopping criteria, and the process of selecting optimal ANN parameters. The final section is a systematic outline of variable reduction by eliminating variables with small weights.

Chapter 5 presents statistical analysis and ANN simulations and evaluates these compared to previous work. The various ANN architecture performance results and corresponding ANN parameters are also presented. The outcomes of the test sets are then analyzed to obtain a representative set of performance measures. The ANN model weights are analyzed and ranked in order of importance and the reduced variable set is produced. Finally, a comparison with previous injury models using the CHIRPP [3] is presented.

The thesis conclusions are presented in Chapter 6, which discloses new findings and modifications. It also outlines the contributions of the thesis and suggests possible future work.

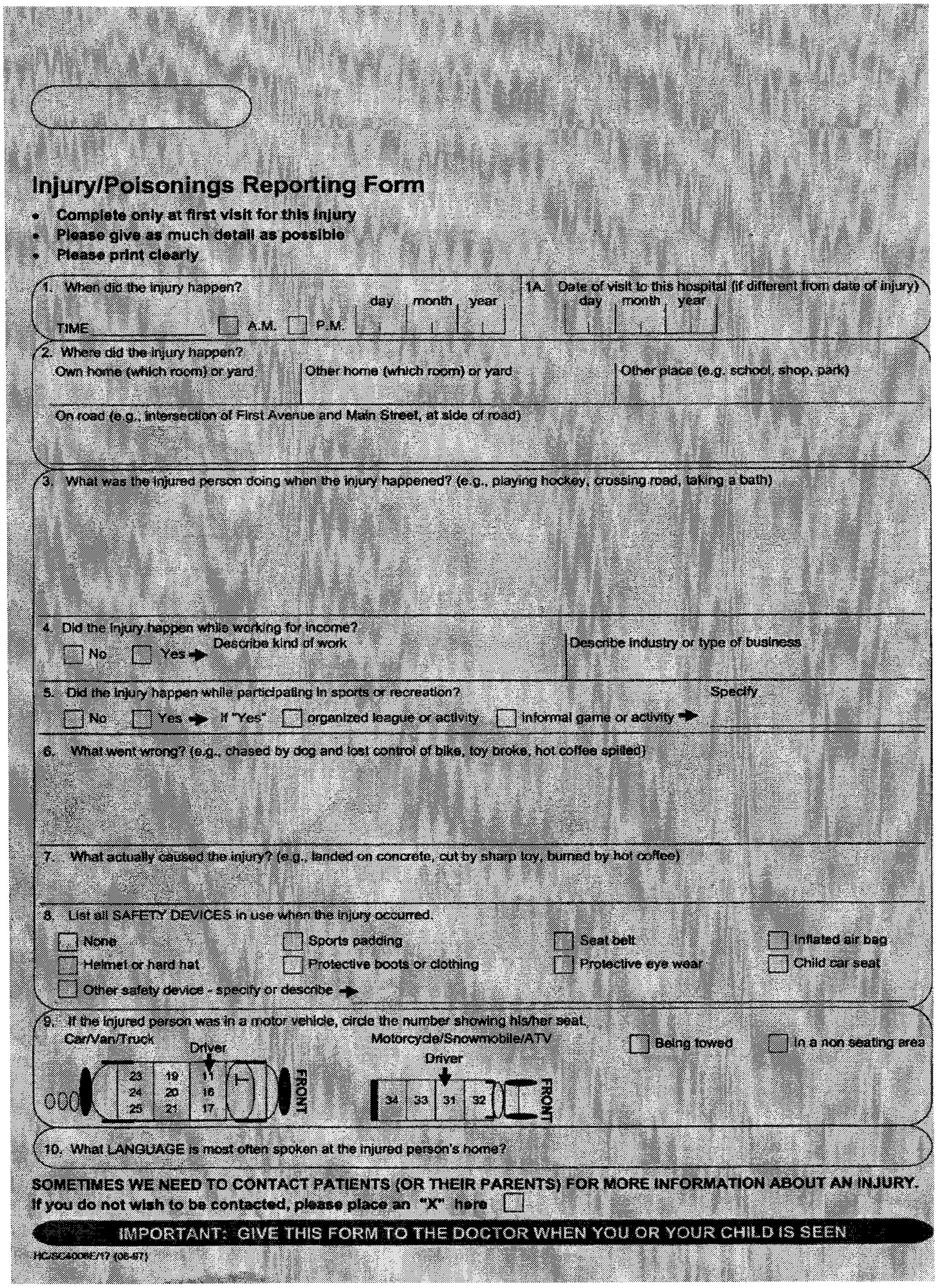
2 Background and Overview of Concepts

2.1 CHIRPP Database

2.1.1 History

In 1990, Health Canada's Child Injury Division (CID) within the Laboratory Centre for Disease Control (LCDC) began a Canadian Hospitals Injury Reporting and Prevention Program (CHIRPP). The injury reporting form (shown in Figure 2.1 and Figure 2.2) is filled out by the patient or guardian in emergency rooms of 10 pediatric hospitals and 5 general hospitals across Canada. As of October 2003, the entire CHIRPP database accumulated 1.36 million injury cases. Before CHIRPP was established in 1990, most of the information collected in Canada about injuries was on hospitalization and mortality rates. CHIRPP fills an information gap by collecting detailed injury information on all types of injuries [4].

The CHIRPP database is mostly from children's hospitals and tends to have fewer older people. A third of the injured victims is less than 5 years old, a quarter is in the 5-9 age group, and a quarter is in the 10-14 age group, whereas the 15-19 age group is only an eighth of the victims [1].



Injury/Poisonings Reporting Form

- **Complete only at first visit for this injury**
- **Please give as much detail as possible**
- **Please print clearly**

1. When did the injury happen? TIME ____ ☐ A.M. ☐ P.M. day | month | year

1A. Date of visit to this hospital (if different from date of injury) day | month | year

2. Where did the injury happen?
Own home (which room) or yard | Other home (which room) or yard | Other place (e.g. school, shop, park)
On road (e.g., intersection of First Avenue and Main Street, at side of road)

3. What was the injured person doing when the injury happened? (e.g., playing hockey, crossing road, taking a bath)

4. Did the injury happen while working for income?
☐ No ☐ Yes → Describe kind of work | Describe industry or type of business

5. Did the injury happen while participating in sports or recreation?
☐ No ☐ Yes → If "Yes" ☐ organized league or activity ☐ informal game or activity → Specify

6. What went wrong? (e.g., chased by dog and lost control of bike, toy broke, hot coffee spilled)

7. What actually caused the injury? (e.g., landed on concrete, cut by sharp toy, burned by hot coffee)

8. List all SAFETY DEVICES in use when the injury occurred.
☐ None ☐ Sports padding ☐ Seat belt ☐ Inflated air bag
☐ Helmet or hard hat ☐ Protective boots or clothing ☐ Protective eye wear ☐ Child car seat
☐ Other safety device - specify or describe →

9. If the injured person was in a motor vehicle, circle the number showing his/her seat.
Car/Van/Truck — Driver — 23 19 11 / 24 20 16 / 25 21 17 — FRONT
Motorcycle/Snowmobile/ATV — Driver — 34 33 31 32 — FRONT
☐ Being towed ☐ In a non seating area

10. What LANGUAGE is most often spoken at the injured person's home?

SOMETIMES WE NEED TO CONTACT PATIENTS (OR THEIR PARENTS) FOR MORE INFORMATION ABOUT AN INJURY. If you do not wish to be contacted, please place an "X" here ☐

IMPORTANT: GIVE THIS FORM TO THE DOCTOR WHEN YOU OR YOUR CHILD IS SEEN

HC/SC4008E/17 (08-97)

Figure 2.1: CHIRPP injury reporting form page 1

PHYSICIAN'S INJURY SUMMARY

- **Complete only for first attendance for this injury.**
- **Please check that the front of the form is complete.**

Physician's Name

1 NATURE OF INJURY

- Select up to 3 codes

Most severe
Second
Third

10 Superficial (e.g., bruise, abrasion)
11 Open wound/Laceration
12 Fracture
13 Dislocation
14 Sprain or strain
15 Injury to nerve
16 Injury to blood vessel
17 Injury to muscle or tendon
18 Crushing injury
19 Traumatic amputation

20 Burn or corrosion
21 Frostbite
22 Bite (with or without invenomation)
23 Electrical injury
24 Eye injury — use body part 135
25 Dental injury — use body part 135
26 Injury to internal organ

31 Foreign body in external eye — use body part 135
32 Foreign body in ear canal — use body part 135
33 Foreign body in nose — use body part 135
34 Foreign body in respiratory tract
35 Foreign body in alimentary tract
36 Foreign body in genito-urinary tract
37 Foreign body in soft tissue

41 Minor head injury — use body part 135
42 Concussion — use body part 135
43 Intracranial injury — use body part 135

50 Poisoning or toxic effect — use body part 900
51 Drowning or immersion — use body part 900
52 Asphyxia or other threat to breathing — use body part 900
53 Systemic over-exertion; heat/cold stress — use body part 900

60 Multiple injuries of more than one nature
70 No injury detected

N.B. For multiple system trauma
(serious injuries of more than 3 types and body parts) use 60 + 700

Is substance use by the patient or other person suspected as a factor in this injury?

☐ No ☐ Yes ☐ Unknown

If Yes: ☐ Alcohol ☐ Other (specify) ______

2 BODY PART(S)

- Write the body part code for each of the injuries in NATURE OF INJURY at left.

Most severe
Second
Third

Head and Neck
110 Scalp, skull, head
120 Face (including ear)
130 Internal mouth
135 Specified head injury (specified by nature of injury)
140 Neck

Spine and Spinal Cord
200 Spine and/or spinal cord

Trunk
310 Thorax (incl. lungs, heart)
315 Upper back
321 Abdomen (incl. abdominal organs)
322 Lower back
323 Pelvis
324 Perineum and anogenital area

Shoulder and Arm
410 Shoulder
415 Clavicle
420 Upper arm
430 Elbow
440 Forearm
450 Wrist
460 Hand
470 Finger

Hip and Leg
510 Hip
520 Thigh
530 Knee
540 Lower Leg
550 Ankle
560 Foot
570 Toe

700 Multiple injuries of more than one body part
900 Body part NOT REQUIRED (e.g. systemic injury, no injury detected)

3 INTENT

- Select one code

10 Accident, injury was not intended
11 Intentional self harm
12 Sexual assault
13 Maltreatment by parent or caregiver
14 Maltreatment by spouse or partner
15 Other or unspecified assault
16 Event of undetermined intent

4 PATIENT DISPOSITION

- Select one code

1 Left without being seen
2 Advice only
3 Treated, follow-up PRN
4 Treated, follow-up required
5 Short stay, observation in emergency
6 Admitted to this hospital
7 Transferred to another hospital (specify) ______
8 Dead on arrival or died in emergency

Figure 2.2: CHIRPP injury reporting form page 2

2.1.2 CHIRPP Database Contents

The CHIRPP database contains the profile of the injured patient and information about the circumstances of the injury. A coding system converts each variable of data into a numeric value.

The main variables recorded by the CHIRPP reporting form are outlined from [4].

- **age:** age separated into age groups: < 1 year; 1 year; 2-4 years; 5-9 years; 10-14 years; 15-19 years; >= 20 years
- **date:** the time, day, month and year the injury occurred
- **gender:** male or female
- **follow-up:** whether CHIRPP is permitted to contact the patient for further information
- **injury location and area:** the location where the injury occurred, e.g. home, school, hospital, sport/recreation facility, street/highway, industrial/construction, mine/farm, etc.
- **context:** what the person was doing during the accident
- **breakdown events:** what caused the injury
- **mechanism:** type of energy, e.g. mechanical, heat, etc.
- **vehicle-seating position:** the seating position of the victim in an automobile, ATV, etc.
- **safety devices:** the type of safety device being used at the time of injury, e.g. helmet
- **nature of injury:** the type of injury, e.g. fracture, laceration, bruise, head injury
- **body part:** body part involved in injury, e.g. head, lower leg, upper arm

- **disposition:** treatment received, i.e. admitted and not-admitted into hospital/fatal
- **intent:** if the injury was intentional (i.e. abuse)
- **work related:** whether the injury was job-related
- **breakdown factor:** gives the object that failed and caused the injury, such as a tree branch breaking
- **mechanism factor:** gives the apparatus that caused the injury itself, such as a ball hitting the person
- **contributing factor:** part of the injury situation but does not cause the injury or breakdown, such as a person falling off a chair – the chair being the contributing factor, it can also be the sport or activity that was taking place at the time of the injury or stimulants taken by the person such as drugs or alcohol

2.1.3 Quality of Database and Limitations

The CHIRPP injury questionnaires collected by hospitals participating in the CHIRPP program are sent to a central office where data coordinators in the LCDC at Health Canada manage the CHIRPP database (the list of hospitals participating in CHIRPP is available in Appendix F). Quality assurance procedures and a high capture rate are a priority. In 1996, it was found that for 14 of the hospitals, the capture rate varied between 24-100% with a median of 88%. There is also software in place that screens for illogical data entries and combinations of entries.

Since the CHIRPP database is mostly from children's hospitals and tends to have fewer older people, comparing the number of injuries between younger and older age groups would not be possible. As well, the population that a particular hospital serves is not available so there is no way to calculate injury rates for any given region. To make regional calculations even more difficult, the hospitals involved in CHIRPP do not usually represent all the hospitals in a city and as a result, the CHIRPP data for a hospital cannot be used to represent injury within that city or for a certain population. Furthermore, there are only 16 out of over 750 hospitals in Canada participating in the CHIRPP; consequently, the CHIRPP data cannot be used to represent the amounts of injuries in Canada. Increasing the number of hospitals that participate in CHIRPP would allow greater regional analysis [1].

In CHIRPP, the injured person or one of their guardians fills out the injury questionnaire. For the most part, having guardians, as opposed to medical practitioners, fill out the form is advantageous since they have the most knowledge about the injury and its circumstances. However, having guardians fill out the forms can produce inconsistent data from one guardian to another where some guardians are not very descriptive or disinclined to answering questions. In order to deal with illiteracy, hospital staff aid in filling out the questionnaire but this can also introduce inconsistency. Often, when parents are unwilling to answer questions, it is because there was intentional injury involved in the incident - medical personnel try to fill as many missing fields as possible. Hospital personnel fill in information on treatment and subsequent injury information.

Other contributions to database inaccuracy include injuries that do not go to emergency rooms for treatment, either because the injuries are of low severity and do not require immediate treatment, or because the patient dies before reaching the emergency room. This inaccuracy may skew the rate of severe injuries reported in CHIRPP, since patients who do not reach the hospital will not be recorded in CHIRPP.

Although most of the participating hospitals are children's hospitals, the data are not representative of children in a particular area because for every child that goes to a children's hospital, there are six children that go to a general hospital. In addition, most of the hospitals participating in CHIRPP are in urban areas; therefore, the data may be unrepresentative of injuries that tend to occur in rural areas [1].

2.2 ATV History

This study focuses on ATV injuries recorded in the CHIRPP database. The Honda Motor Company manufactured the first ATV. The American Honda Motor Company gives the history behind the ATV:

> "[The ATV] was initially developed in Japan as a farm-to-town vehicle in isolated, mountainous areas. During spring thaws and rainy seasons, steep mountainous roads were often impassable with conventional vehicles. The three-wheeled ATV proved to be a much better mode of travel and soon became a recreational vehicle, providing transportation to areas inaccessible by other motorized transport. And, it wasn't long before the Japanese manufacturers realized that the ATV could be sold to Americans. When the ATV first appeared in the United States in the early 1970's, it was promoted and sold as a recreational vehicle designed to provide "thrills" for the rider. This is still its primary use today. Shortly, however, sportsmen found that the ATV was a useful machine to move through areas not accessible with pick-up trucks, four-wheel drives, or other motorized vehicles. The ATV became popular as a hunting vehicle and was used to reach remote areas and to transport game back out."

2.3 ATV Related Injuries

ATV injury is on the rise according to a Journal of the Canadian Paediatric Society statement, which called to attention 2535 ATV-related hospitalizations in 2000-2001, which is 50%

more than 1996-1997. The impact on children aged 5 to 19 is particularly high - accounting for 36% of hospitalizations. The CHIRPP database lends itself well to a study of ATV injuries since many ATV injuries involve children. The U.S Consumer Product Safety Commission found that 40% to 50% of ATV injuries and 35% of ATV deaths are children less than 16 years old. A similar scenario can be found in Canada, where 25% of ATV deaths are children less than 16 years old. Furthermore, 36% of ATV injuries in the CHIRPP database are severe in nature. The following is background information about ATVs, ATV injury statistics and ATV prevention initiatives.

2.4 Children, ATV Operation and Legislation

ATVs are motorized vehicles that are used for occupation, recreation and transportation. They have three or four wheels and come in a variety of sizes. They range in weights up to 273 kilograms and have engines with 50 to 700 cubic centimeters (cc) of displacement [8].

The attributes of children and youth often hinder their ability to operate ATVs safely. They may have deficiencies in knowledge, physical size and strength and motor skills. A minimum physical size and strength are necessary to operate a full-sized ATV properly. In fact, there are voluntary standards by the Canadian ATV industry for children under 12 years old advising them against riding ATVs of 70 cubic centimeters (cc) or more and for any child under 16 years of age against riding ATVs of 90 cc or more. Furthermore, recent manuals and standard labels have warnings that people younger than 16 years of age have a greater risk of death and of having a severe ATV injury [7]. Children and youth are also less likely to use helmets and are more likely to perform unsafe actions such as riding double and driving ATVs on public roads. Despite the aforementioned facts, the legislation restricting the minimum age of ATV operators is mostly non-existent as shown in Table 2.1 from the Journal of the Canadian Paediatric Society [8]. It is interesting to note that helmet use is usually required in most provinces, yet according to the

CHIRPP data, a significant amount of ATV injury patients did not indicate they were wearing a helmet (Table 5.9).

Table 2.1: ATV legislation on driving age and helmet use requirements

Province	Minimum Driving Age	Helmet Required
Alberta	none	yes
British Columbia	none	no
Manitoba	none	yes
New Brunswick	none	yes
Newfoundland	none	yes
Northwest Territories	none	yes
Nova Scotia	none	yes
Nunavit	none	yes
Ontario	none	yes
Prince Edward Island	6 years	yes
Quebec	14 years	yes
Saskatchewan	none	yes
Yukon	none	yes

2.5 ATV Safety Recommendations and Legislation

Helmet use was found to be 78.4% in a study of 264 ATV riders in the U.S. The study also found that riders who wore helmets were more likely to wear other protective gear. Furthermore, the study found that those who took ATV training courses wore helmets 4.3 times more than those without any formal ATV training did. There are still many ATV riders who do not wear helmets despite the fact that helmet use is mandatory in all provinces except British Columbia [9].

Most ATVs are not designed to carry passengers and therefore passengers can adversely affect balance and steering. There are also warning labels on new ATVs restricting any passengers; yet, many ATV injuries happen to ATV passengers. Studies of childhood injuries show that 15 to

30% of injuries occurred while there was a passenger. ATVs are often used to transport children in First Nation's communities and in rural communities [10, 11].

2.6 ATV Injury Demographics

Males are involved in 75 to 85% of ATV accidents [12, 13]. A third of emergency room visits and 30% of hospitalizations are for victims less than 16 years old. In addition, half of all deaths due to ATV injuries are in the 16 and under age group. ATV injuries occur more often during the day and on weekends and holidays. Driver error, poor judgment and loss of control usually cause them. There is a three times greater risk of injury with three-wheeled ATVs because they are less stable than four-wheeled vehicles [14, 15].

2.7 Protective Gear and ATV Passengers

In the 1980's, the Canadian Paediatric Society and American Academy of Pediatrics recommended that children should not use ATVs and they recommended the introduction of ATV legislation such as a minimum age requirement to operate an ATV, a helmet requirement and licensing and insurance requirements [16]. Legislation proved to be an effective tool in ATV injury prevention. In a comparison of six American states, from 1990 to 1999, states without any ATV legislation had double the mortality rate [17]. In the U.S., selling three-wheeled vehicles was restricted in 1988. The American ATV industry also introduced voluntary standards, warnings, training courses, minimum age requirements on ATV use and minimum age requirements on target audiences for advertising [18]. These past prevention practices resulted in a decline of ATV injuries until the early 1990's. On the other hand, a study from 1998 to the year 2000 by the U.S Consumer Product Safety Commission found that ATV injuries are on the rise for both adults and children [19].

The Journal of Canadian Paediatric Society has recently made seven recommendations in an effort to prevent ATV injury [8]:

1. An age requirement of 16 or older to operate ATVs.

2. The restriction of passengers on ATVs unless the ATV is designed for passengers.

3. The use of government-approved helmets as well as eye protection, boots, long pants and gloves.

4. The restriction of driving ATVs under the influence of alcohol and at night.

5. The completion of a certified ATV training course by ATV operators.

6. Changes to ATV vehicle design to improve vehicle safety with a focus on rollover protection, seatbelts, and speed governors to directly limit ATV speeds.

7. A collaboration of similar legislation across Canada to enforce a minimum age requirement of 16 years of age, no passengers, helmet use, training, licensing and the restriction of three-wheeled vehicles.

3 Literature Review and Choice of Approach

This chapter describes the reasoning behind the proposed methodology and solutions in creating an injury severity prediction model. The first section describes statistical analysis methods and the use of ANNs for analysis. The following sections elaborate on ANNs as an aid to make clinical decisions and methods to improve ANN performance. In addition, there is a review of relevant work to predict repeat injuries using ANNs with CHIRPP data. The last section of this chapter provides the reasoning for the proposed approach.

3.1 Statistical Data Selection

Statistical methods of selecting significant input data often use correlation to find the relationship between variables. Bivariate correlation is a measure of the correlation between pairs of variables and univariate correlation is a measure of the correlation between the input and outcome. Researchers often remove insignificant variables before working with a dataset [20]. Researchers may also remove input variables that are highly correlated to the outcome before generating a model because the correlation has already revealed the predictive capability of the input to the outcome and may adversely affect the modeling technique [21]. However, the ANN naturally finds the significant variables; therefore, the correlation information is not used to remove variables. As indicated earlier, bivariate correlation is used to sustain ANN findings.

3.2 Statistical Analysis Methods

Artificial neural networks and statistical modeling techniques such as logistic regression and Bayes' modeling are common methods of analysis in biomedicine. The number of publications in Medline, a monthly publication of life science and biomedical articles by the U.S. National Library of Medicine (NLS) that has a compilation of 11 million records online, shows the number of publications for data handling as follows:

- logistic regression: 28,500
- artificial neural networks : 8,500
- k-nearest neighbors: 1300
- decision trees: 1100
- support vector machines: 100

Modeling techniques using logistic regression, Bayes' theorem and ANNs were explored, as described below, and ANN analysis was chosen to create an ATV injury model.

3.2.1 Logistic Regression

Logistic regression is the most popular statistical technique of regression analysis in medical research. Logistic regression estimates the probability of the outcome as a dependent dichotomous (divided into two parts) variable. The input factors, also called risk factors, are independent variables [23]. Logistic regression collects information about the actual outcomes of patients and uses these outcomes to calculate regression coefficient parameters to model the results. The regression coefficients are calculated by analyzing the outcomes of a training set of patients with various combinations of risk factors. The analysis of the training set of patients increases the probability that a matching set of risk factors will have the same outcome when the model is tested [22]. The logistic model is represented by the probability of a response:

$$P_r(\mathrm{Response} \mid x) = \frac{1}{1 + e^{[-\beta_o + \sum_{j=1}^{k} \beta_j x_j]}} \tag{3.1}$$

where β represents the regression coefficients and x represents the inputs.

The two outputs are a response or the absence of a response. The logistic function is a non-linear function represented by an S-shaped curve. The x-axis is the explanatory independent variable and the y-axis is the dependent response variable that lies between zero and one [24].

Logistic regression can be used to create an injury model; however, it requires greater pre-processing of variables than ANN analysis.

3.2.2 Bayes' Theorem

Bayes' theorem can be used to create a distinctive statistical model that calculates conditional probabilities. The probability of the outcome is conditional in Bayes' model because it depends on the existence of certain risk factors or priors. The advantage of Bayes' model is that it takes into account the fact that certain conditions (i.e. priors) affect the probability of the outcome. The conditional outcome, known as the posterior probability is defined as the probability of A given B, P[A|B], shown in equation (3.2) where '~' represents the inverse or 'not' [25].

$$P[A \mid B] = \frac{P[B \mid A] * P[A]}{P[B \mid A] * P[A] + P[B \mid \sim A] * P[\sim A]} \tag{3.2}$$

For ATV injuries, the outcome of a severe injury is the posterior probability and the major risk factors for a severe injury occurring are the priors. The major risk factors for severity are found using regression analysis. Bayes' outcome probability is calculated according to P_i [20].

$$P_i = \frac{\prod_{j=1}^{J}\{a_j P(S_j \mid D_i) + (1-a_j)[1-P(S_j \mid D_i)]\}P(D_i)f(P)}{\sum_{i=1}^{I}\prod_{j=1}^{J}\{a_j P(S_j \mid D_i) + (1-a_j)[1-P(S_j \mid D_i)]\}P(D_i)} \tag{3.3}$$

$P(D_i)$ represents the priors,

$P(S_j|D_i)$ represents the posteriors,

P_is= the outcome probability for each output,

D_i = the actual output,

S_j = the input risk factor,

f(P) = the exponential correction factor,

a_j=1; if the risk factor S_j exists and

a_j=0; otherwise.

Bayes' theorem is similar to logistic regression for the reason that it requires greater pre-processing of variables than artificial neural networks. Statistical modeling techniques are used to obtain information about important variables whereas ANNs can create models that predict outcomes on a case by case basis. ANN analysis is described in detail in the following section.

3.3 Artificial Neural Network Analysis

An artificial neural network's computation behaves similarly to the human brain, as it is a nonlinear parallel process consisting of many small logical units. The brain has billions of these logical units called neurons connected to each other by weighted connections called synapses. An ANN learns through training similar to the way the brain learns. The first stage of a neural training algorithm involves training the ANN to learn from its environment. During training, synaptic weights in an ANN are adjusted until the output of the ANN closely resembles the known output for the particular input data set. Once the ANN is trained, it is tested using an input set to which it was never exposed. A correctly trained ANN should be able to predict the output of the new input set with a high rate of success.

The ANN software program accepts a set of training data and uses a performance measure, i.e. the true positive rate (sensitivity), the true negative rate (specificity) or the logarithmic-sensitivity index as a stopping condition. Once the stopping condition is satisfied, a set of test data is applied to the ANN (performance measures are discussed in more detail in Chapter 4). Figure 3.1 shows the basic architecture of a two-layer ANN from [2].

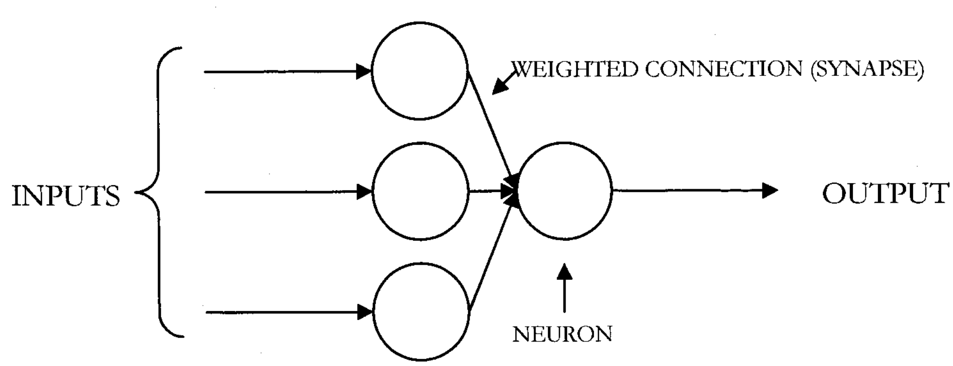


Figure 3.1: Basic architecture of a two-layer ANN

3.3.1 ANN Functionality

The ANN learning process assigns values to synaptic weights, w_{kj} , where 'j' is the source node and 'k' is the end node. These synaptic weights are what can be described as retained knowledge of the ANN. The input signals, x_j, a bias term, b_j, are multiplied by these synaptic weights and summed by a linear combiner resulting in u_k as shown in equation (3.4).

$$u_k = \sum w_{kj} x_j + b_j \tag{3.4}$$

The corresponding products and the bias input are processed by an activation function, $\varphi(\cdot)$ [2]. The activation function used in this ANN is the hyperbolic tangent transfer function:

$$\tanh x = \frac{e^{2x} - 1}{e^{2x} + 1} \tag{3.5}$$

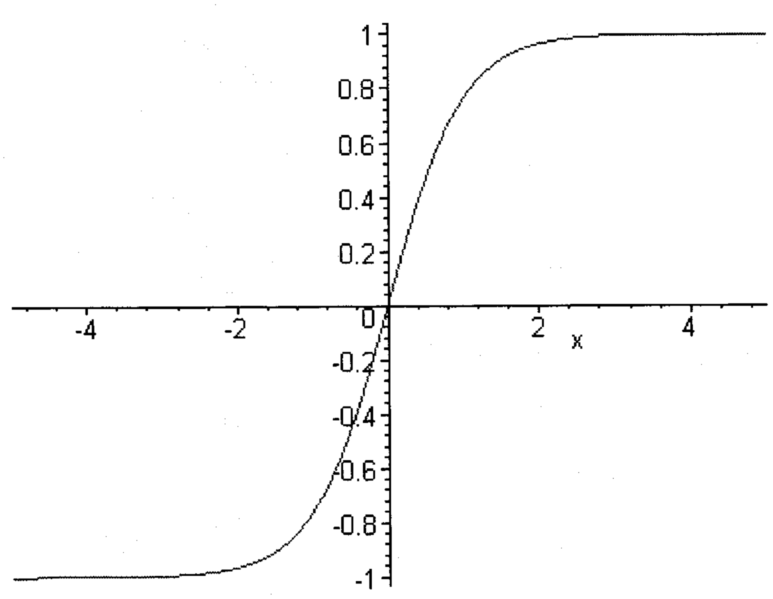


Figure 3.2: Hyperbolic tangent

The hyperbolic tangent is a nonlinear, continuous and monotonically increasing differentiable function ranging from -1 to 1. Figure 3.2 shows that the nonlinearity of this function results in very little change after the saturation point [26]. Furthermore, the S-shaped hyperbolic tangent function has a steep slope around zero resulting in a greater amount of non-zero outputs. It has a highly desirable clear transition between output values, which results in a faster learning process [27]. It has been found that a faster learning process will ensue when the output is between –1 to 1 and the inputs are scaled to a unit variance with a mean of zero [28].

The corresponding output y_k, is processed by the activation function as shown by Figure 3.3 and the following equation (3.6):

$$y_k = \varphi(u_k + b_k) \tag{3.6}$$

x_j = the inputs into the ANN.,

w_{kj} = the synaptic weights ,

k = the neuron and j synaptic connection

b_k = the bias input.

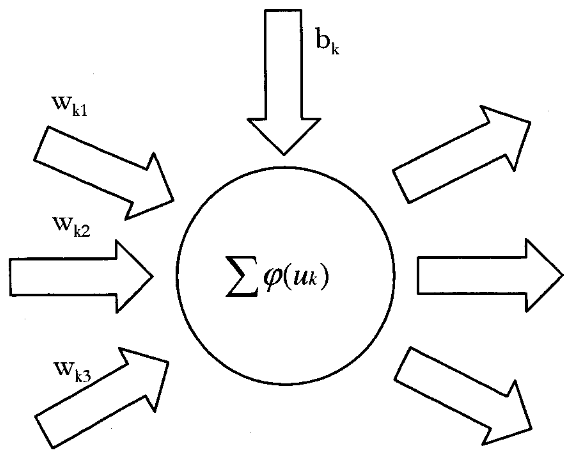


Figure 3.3: Activation function calculation taking place at each neuron

The input into the ANN consists of a patient data matrix. Each row in the matrix represents a separate patient case and each column of the matrix represents a variable containing information about the patient and their injury as well as the outcome of interest (i.e. injury severity). For an n-layer ANN, the output of the ANN is given by A_n in the following equation; where p is the number of inputs going into each individual node.

$$A_n = \tanh\left(\sum_{i=1}^{p} W_n[i]A_{n-1}[i] + b_n[i]\right), n \geq 1 \tag{3.7}$$

In the ATV injury study, the input matrix of patient data is A_0 and the predicted output by the ANN of outcomes is the output matrix A_1. The ANN output predictions vary anywhere between -1 and 1 where the range less than 0 is one outcome and greater than zero is the other outcome. The actual outcomes in the data matrix have a different data representation of either -1 or 1. The difference between the predicted outcome and the actual outcome is the error [30, 31]. The goal of training an ANN is to find a set of weights that result in the least possible error.

3.3.2 Types of Artificial Neural Networks

There are single-layer and multi-layer feed forward ANNs. The type of ANN used in this work was restricted to a feed forward ANN since none of the outputs needed to be fed back into the network. In a single-layer ANN, the input layer is directly connected to the output layer. In a multi-layer ANN, there is at least one hidden layer of neurons between the input and output neurons. The hidden neurons play the role of calculating higher-order statistics and can work with processes that are more complex; however, having greater than one hidden layer does not necessarily result in a higher performance ANN. In fact, most ANNs used in clinical medicine use one hidden layer because these networks can correctly approximate smooth linear functions, which usually result from medical data [28]. The Medical Information-technology Research Group (MIRG) has demonstrated the high performance of ANNs in clinical medicine at the University of Ottawa and Carleton University. Studies in this group that achieved high performance using one hidden layer include Ennett's model for predicting coronary surgery mortality [29] and Shi's model for predicting repeat childhood injury using ANNs [3].

3.3.3 Back-propagation and Hidden Layers

A two-layer ANN only has one layer of weights and the error signal (containing the difference between the predicted outcome and the actual outcome) does not need to be sent back through multiple layers to adjust the weights. However, in a multi-layer network it is necessary to have a method of sending the error signal back through each layer. In order for the weights at each layer to be adjusted to improve network error, the error signal travels back through the layers through an error back-propagation algorithm. For a multi-layer ANN, there is a forward computation and a backward computation. The forward computation for each layer results in:

$$u_j^{(l)}(n) = \sum w_{ji}^{(l)}(n) y_i^{(l-1)}(n) \tag{3.8}$$

where 'w_{ji}' is the synaptic weight from neuron 'i' to neuron 'j' and 'y_i' is the output of the previous layer. 'l' refers to each layer in the network and (l-1) refers to the previous layer at iteration 'n'.

Once the forward computation is complete, the output error is calculated and back propagated. Back-propagation is carried out using the delta rule represented by equation (3.9) to change each weight for the next iteration [2].

$$w_{ji}^{(l)}(n+1) = w_{ji}^{(l)}(n) + m\left[w_{ji}^{(l)}(n-1)\right] + \eta\delta^{(l)}(n)y_i^{(l-1)}(n) \tag{3.9}$$

where 'n' is the iteration, 'l' refers to a particular hidden layer, m is the momentum, δ is the local gradient and η is the learning rate.

3.3.4 Optimization using the Steepest Descent Method

The synaptic weights of the ANN are adjusted until the error in the prediction of outcomes is minimal. A cost function is used as a measure to find the optimal weights:

$$\frac{1}{2}\sum e^2(n) \tag{3.10}$$

where $e(n)$ is the error at epoch n (one epoch is an iteration in which the entire training data set is interpreted by the ANN).

The steepest descent algorithm is an adaptive filtering algorithm that uses the cost function and adapts its parameters to find an optimal solution. It finds the adjustments to the weights of the network by taking steps towards the minimum along the error function that are proportional to the gradient at points along the function. The change in weights is done according to the steepest descent method by:

$$w(n+1) = w(n) - \eta g(n) \tag{3.11}$$

where η is the learning-rate parameter and g(n) is the gradient at w(n) from iteration n to n+1 [30].

The learning rate parameter is used to determine how quickly each step approaches the minimum. The learning rate can either be established by adjusting the learning rate to minimize the performance index at every iteration, simply assigning fixed learning rates, or by using variable learning rates such as η_k=1/k where k is the variable. When adjusting the learning rate to minimize the performance index, the performance index is minimized over: $w(n) - \eta g(n)$.

The gradient is calculated with respect to each weight in order to determine how changes in weight influence the total error. Each point 'p' along the error function contributes an error 'E_P' as defined in (3.12) where:

$$E_{TOTAL} = \sum E_P \tag{3.12}$$

$$E_P = 1/2 \sum (t_o - y_o)^2 \tag{3.13}$$

't', is the target output and 'y', is the actual output

The gradient can be calculated for each point:

$$\frac{\partial E_{TOTAL}}{\partial w_{ji}} = \frac{\partial \sum E_p}{\partial w_{ji}} = \sum \frac{\partial E_p}{\partial w_{ji}} \tag{3.14}$$

The gradient can be simplified as follows from [2]:

$$\mathrm{E}(w) = \frac{1}{2} e^2(n)$$
$$\frac{\partial \mathrm{E}(w)}{\partial w} = e(n) \frac{\partial e(n)}{\partial w}$$
$$e(n) = y(n) - x(n)w(n)$$
$$\frac{\partial e(n)}{\partial w(n)} = -x(n)$$
$$\frac{\partial \mathrm{E}(w)}{\partial w} = e(n) \frac{\partial e(n)}{\partial w(n)}$$
$$\frac{\partial \mathrm{E}(w)}{\partial w} = -x(n)e(n) \tag{3.15}$$

The total gradient is found by summing the gradient for each data point. The weights in the network are updated to approach a minimum gradient. Once the network has found a minimum, it is said to have converged.

The gradient is substituted into the steepest descent equation, which results in the resulting LMS algorithm as represented in the equation.

$$w(n+1) = w(n) + \eta\big(x(n)e(n)\big) \tag{3.16}$$

where x(n) is the input vector and e(n) is the error.

It is important not to make the learning rate too large as this may result in missing the minimum or create an unstable algorithm; however, the learning rate cannot be too small or it will take much longer for the error to converge. In practice, the learning rate is assessed over a range of possible values so that the global minimum can be found within a stable algorithm [30].

3.3.5 Weight-elimination

The weight-elimination and weight decay terms are added to the error function used in the back-propagation algorithm to adjust the weights of the network. Weight-elimination reduces the weighting of connections to zero if they are not a substantial weight. The reasoning behind eliminating connections with low weighting is that they are not significant in predicting the outcome and can adversely affect the results by adding noise to the system. In addition, weight-elimination reduces the input variable set to include only the larger weights and thus simplifies the ANN, which improves the performance [33, 34, 35].

Weight-decay restricts the weighting on connections in the network, which limits the variance of the output and produces a more stable network. Weight-elimination and weight-decay help to avoid over-fitting during network training. Over-fitting occurs when the network begins to use memorization of prior outcomes for prediction.

The back-propagation algorithm error function sums the total error for each node in the network. The weight elimination term is added to this function to eliminate a greater number of connection weights and to keep the overall error low. In the following formula, E(W), is a combination of the back-propagation error $E_o(W)$ and the weight elimination error where W is the weight vector. In the weight elimination term, λ is a weight-decay constant, w_{ji} represents each weight in the network and w_0 is a weight decay scaling value.

$$E(W)=\sum_{i=1}^{p}(E_0(W))^2+\lambda\sum_{ji}\frac{\frac{w_{ji}^2}{w_0^2}}{1+\frac{w_{ji}^2}{w_0^2}} \tag{3.17}$$

The weight decay constant, λ, affects the impact of the weight elimination term. A higher weight decay constant requires the weighted connections to be closer to zero before they can be eliminated but it also forces the weights that are close to zero to be eliminated. The weight decay constant is set to zero until the network has collected enough input information and is slowly decreased to find the optimal network performance [33].

The weight-decay scale factor, w_0, establishes the magnitude of the weights that will be affected by weight-elimination. A smaller scale factor will result in a higher cut-off weight and greater weight-elimination, whereas a larger scale factor will result in a greater amount of smaller weights but will restrict the size of the large weights [33].

3.3.6 Optimizing the ANN

The ANN parameters are adjusted during training for optimization of the ANN. The main parameters include the error ratio, learning rate, weight decay constant and momentum. The change in the learning rate is incremented and decremented by adjusting the learn rate increment and decrement parameters. The weight decay constant is adjusted using weight decay increment and decrement parameters.

Equation (3.18) describes the change in weight, dW [30]. Where m is momentum, lr is learning rate and $\frac{dE}{dy}$ is the change in error.

$$dW_n = m * dW_{n-1} + lr * (1 - m) * \frac{dE}{dy} \tag{3.18}$$

The error ratio is used to adjust the learning rate, weight decay and momentum parameters. After each epoch, the product of the previous training set error and error ratio is compared with the current training set error. If the current training set error is greater than the product of the previous training set error and error ratio, then the learning rate and weight decay parameters are decremented and the momentum is set to zero. However, if the current training set error is less than the product of the previous training set error and error ratio, then the learning rate and weight decay parameters are incremented [33].

3.4 Comparison of ANNs to Fuzzy Logic Classifiers

A comparison of ANNs to Fuzzy Logic Classifiers was made by MIRG [36]. Fuzzy Logic is an artificial intelligence application that has been proven to work well in analyzing medical data. The type of fuzzy pattern classifier used by this comparison is known as the Fuzzy K-nearest Neighbor (FK-NN) algorithm. The FK-NN algorithm places the outcome into classes and assigns a degree of certainty to the classification. The comparison utilizes a perinatal database from 2001, which was obtained from the Perinatal Partnership Program of Eastern Ontario (PPPSEO) with 16,183 patient cases and 39 input variables. The study analyzes the ability of the ANN and FK-NN to predict the neonatal outcomes of delivery type (Caesarian section/Vaginal), Apgar score, and death. The performance measures include correct classification rate (accuracy), sensitivity (the ability to correctly classify positive outcomes) and specificity (the ability to correctly classify negative outcomes). The results show that the correct classification rate and specificity performance measures are above 85% for all outcomes using both methods of analysis. However, Table 3.1 shows that the ANN has a higher sensitivity than the FK-NN for all of the different outcomes.

Table 3.1: Comparison of the sensitivity of ANN to FK-NN

Approach	Delivery Type Sensitivity (%)	Apgar Score Sensitivity (%)	Mortality Sensitivity (%)
ANN	80.6	31.36	90.0
FK-NN	71.25	19.49	55.0

This section described a comparison between ANNs and Fuzzy Logic Classifiers in the analysis of medical data and explained why feed-forward back-propagation ANNs were the choice of approach.

3.5 Related Works Involving ANNs

This section explains the benefits of ANNs in medical environments and gives examples of previous work that used ANNs to predict outcomes with medical records.

3.5.1 The Use of ANNs for Clinical Decisions

There are many medical devices in intensive care units (ICU) that produce a large amount of data for interpretation by medical personnel; however, there is not always time for interpretation especially in critical situations. In an attempt to overcome this problem, an investigation into the use of ANNs as a tool to predict clinical outcomes to aid in clinical decision-making was carried out by Trigg [37]. Trigg also explored methods on improving ANN performance using: weight-elimination, reducing the complexity of the ANN architecture, and reducing the effects of the lop-sided outcome distributions [37].

The database used to analyze ANNs as a clinical decision-making tool consisted of administrative and clinical parameters for 3000 patients who were admitted to the ICU at the Doctor Everett Chalmers Hospital (DECH) in Fredericton, NB, Canada. A portion of this larger database with 51 input parameters and 1491 cases in total and more complete data were used in the ANN analysis. Feed-forward ANNs consisting of two and three-layer network (one hidden layer) architectures were trained using the back-propagation algorithm. The database was separated into postoperative and non-postoperative, which refers to patients who were admitted after surgery and those who were admitted for non-surgery-related reasons. The three outcomes predicted by the ANN were mortality, artificial ventilation time and length of stay in the ICU.

The performance measure of the ANN was the correct classification rate (CCR), which is defined as the correctly predicted outcomes divided by all the outcomes. The CCR is compared to a constant predictor (CP), a statistical indicator, which is the percentage of the outcome with the higher *a priori* probability.

Trigg's study found that the ANN performed better with the weight-elimination cost function than without for two and three-layer ANN architectures. The two-layer ANN with weight elimination had a CCR of 19.4% higher than the CP did and 4.4% higher than the Bayes' classifier. The three-layer ANN had a CCR of 20.7% higher than the CP did and 5.7% higher than the Bayes' classifier.

The network complexity was reduced from 51 input parameters to six parameters with the most prevalent weights for a two-layer network. When the network complexity was reduced it had a CCR of 90.5%, which is 18.1% higher than the CP of 72.4% for this network. The network with six inputs stabilized in 130 epochs, whereas the network with 51 inputs took 394 epochs to stabilize. Hence, a less complex ANN has a higher performance and is easier to implement because the medical personnel have fewer parameters to enter into the system. Lastly, when the outcome distribution was varied over a range from 50.8% to 98.1%, it reduced the ANN's ability to reach a CCR higher than the CP, which indicates that a lop-sided output distribution reduced the CCR's ability to measure the performance of the ANN [37].

3.5.2 Predicting Repeat Injuries using ANNs with CHIRPP

The first investigation of the CHIRPP database using ANNs was developed by Shi [3] to predict the repeat of childhood injuries. The ANN architecture used in Shi's study was chosen based on MIRG's experience, which demonstrated the high performance of a feed-forward ANN with a back-propagation algorithm. An evaluation of various layers of ANNs and numbers of hidden layers resulted in the choice of both single and double-layered network architectures.

Shi's analysis used the CHIRPP database from 1990 to 2001, consisting of 125,493 patients with 14 input parameters, to predict whether there would be a childhood injury or not. A weight-elimination cost function was used to reduce weights and find parameters that had the most influence on the outcome. However, due to the complexity of the network, another technique was chosen whereby each parameter was removed one at a time while keeping all other parameters constant to assess the performance of the network could be found with each parameter removed. The input variables were then ranked according to the performance of the ANN and hence according to the impact they had on predicting the output. The ANN was able to predict with accuracy of 80% if a patient would have a repeat injury. The study showed that ANNs are a viable method of analysis in clinical environments and in the prediction of childhood repeat injuries [3].

The optimal architecture of the repeat childhood injury ANN was found to be a three layer ANN consisting of one hidden layer and five hidden nodes. The ANN model required a multi-layer ANN to deal with the database's complex nature [3]. The performance of the repeat injury model is given in Table 3.2. The repeat injury model achieved a sensitivity of 69.3% and a specificity of 71.6%. The classification rate was 70.5%, which is 16% higher than its constant predictor is. The ROC curve is a plot of sensitivity versus one minus specificity and it represents the probability of positively predicting a severe injury versus the probability of positively predicting a non-severe injury. The repeat injury model measured an ROC area of 0.8096, which reflects its high sensitivity performance measure.

A particular modeling technique may not result in the same level of performance for every database [53]. Although both the ATV severe injury and repeat injury databases contain information from the main CHIRPP database, they contain diverse subsets of variables, which have both binary and continuous data types. In addition, the repeat injury database contains every type of injury and thus almost every patient; however, the ATV severe injury database is a narrower subset of patients who experienced ATV injuries. The ATV database is a subset of the main CHIRPP database and contains 2927 patient cases as opposed to the 125,493 patient cases used for the repeat injury model. Training the ANN with a larger number of patients increases the number of less frequent outcomes, i.e. severe outcomes, which the ANN can use to improve its performance in predicting outcomes [29]. High performance can be attributed to a set of input variables that have a highly decisive influence on the outcome.

Table 3.2: Performance of the repeat injury model

Performance Criteria	Repeat Injury Analysis
Sensitivity (%)	69.3
Specificity (%)	71.6
CCR (%)	70.5
ROC Area	0.8096
Constant Predictor (%)	54
Epoch	3462

The final network parameters for the repeat injury model are in Table 3.3. On observing the weight elimination terms, the weight decay constant (λ) is very close to zero at a value of 0.0000032. The weight decay constant and weight elimination product is intended to force smaller weights to zero and reduce larger weights. Larger values of the weight decay constant will amplify this effect. The very small weight decay constant in the repeat injury model indicates that weight elimination played a small role in the error cost function and the adjustment of the weights on the ANN connections.

Table 3.3: ANN network parameter values of the repeat injury model

model	lr	lr_inc	lr_dec	λ	λ_inc	λ _dec	w_o	mmtm	error ratio
repeat injury	0.0045	1.004	0.7189	3.2E-06	1.001	0.999	0.003	0.964	1.030

The weights of the repeat injury model were also analyzed and used to rank the input dataset in Table 3.4.

Table 3.4: Input dataset rankings for the repeat injury model

Ranking [highest- lowest]	Repeat Injury database
1	body part
2	disposition
3	nature of injury
4	breakdown
5	age group
6	sex
7	location
8	day
9	follow-up
10	mechanism

3.6 Injury Severity Model Research Question

The injury severity model uses an ANN with a specific set of patient attributes and injury information to predict whether a person will have a severe injury. The weights of the ANN are also analyzed to find the dataset that strongly predicts the outcome. In the previously discussed applications, ANNs were used to aid in clinical decision-making by predicting mortality in neonatal intensive care units, and to predict the repeat of injuries with the CHIRPP database. These successful applications of ANNs prompted more analysis of the CHIRPP database – in this case with respect to ATV injuries. An in-depth study of ATV injuries was selected based on the observation that there are an increasing number of ATV injuries and the severity of ATV injuries is higher than most other forms of injury. In fact, 36% of ATV injuries are severe injuries and finding the dataset that strongly predicts severe injuries may aid injury prevention and prompt ATV manufacturers to create safer vehicles.

4 Statement of the Problem and Methodology

This section gives the problem statement and describes the methodology carried out to solve the problem. The methodology includes: data groundwork, performance testing preparation, statistical analysis, ANN software, training and testing, ANN optimization, variable reduction and knowledge translation and exchange.

4.1 Problem Statement

The objective of this thesis is to:

- Test utilization of an ANN to translate the CHIRPP database obtained from Health Canada's Injury and Child Maltreatment Section in the Health Surveillance and Epidemiology Division with the purpose of providing information to injury prevention programs on the factors that are important in predicting all terrain vehicles (ATV) injury severity,

- Find out if a statistical analysis, frequency analysis and correlation, can uphold the ANN results and

- Provide conclusions and recommend future work to improve the applicability of ANN.

The factors that are of great importance in predicting ATV injury severity are found through weight-elimination and variable reduction. Variable reduction extracts variables without deteriorating ANN performance to find a minimal set of variables that can confidently predict the severity outcome. This method is tested through statistical analysis of the factors that the ANN finds to be key in predicting the severity outcome.

The ANN model of ATV injury severity is based on the current ATV-related data from the CHIRPP database. It is limited to the prediction of outcomes of present data and retraining of the ANN is recommended if a large amount of data is introduced. For example, once the CHIRPP data for 2002 to 2005 becomes available, you would retrain the ANN to validate the new ATV injury severity model.

4.2 Data Preparation

A complete list of all the variables in the original CHIRPP database and its data format can be found in Appendix A. Most text-based variables were not directly used as inputs into the ANN; however, they were used to verify numerically coded data and to fill in missing information. The ATV CHIRPP database variables received from Health Canada were slightly different from the original CHIRPP database because some of the general injury variables were not applicable to ATV injuries.

The data used as input to the ANN must not have missing information in any patient record. There are several options for dealing with missing information such as: imputing a value based on the mean value of other patient records, gathering missing values from the text description of the incident, excluding the patient record, or if the value is missing from multiple patients' records, excluding the entire variable altogether. Initially, a frequency analysis of missing values from each variable was carried out. Table 4.1 shows all the variables in the ATV database and the corresponding amount of data values missing. The missing value frequency analysis showed that contributing factor 2 and breakdown factor 2 have more than 80% missing data; breakdown factor 1 has 65.5% missing data; and contributing factor 1 has 52% missing data. Frequently, when a breakdown factor value does not exist, then a contributing factor usually does and vice versa. Only 20 out of the 4288 cases (0.47%) have values for both the breakdown and contributing factor simultaneously.

Table 4.1: Missing values for the ATV database

Variable	Amount of Missing Values (%)
Sex	0
Age	0
Ethnicity	36.5
Day (of week)	0
Month	0
Year	0
Hour	16.8
Location	37.1
Area	57.3
Context	2.4
Job Related	0
Industry	96.8
Occupation	96.3
Breakdown	2.1
bf1 (breakdown factor)	65.5
bf2	84.9
Mechanism	0.1
mf1 (mechanism factor)	0.1
mf2	82.6
cf1 (contributing factor)	52
cf2	92.3
Vehicle Seat Position	26.3
sd1 (safety device)	56.8
Follow-up	0
ni1 (nature of injury)	0.9
bp1 (body part)	0.9
ni2	73.9
bp2	73.9
ni3	89.3
bp3	89.4
Intent	0
Severity	0
Rural	0

In a joint effort with Health Canada, the incident description text fields were used to fill-in information for other missing fields and to create new fields that are more comprehensive. During this endeavor, the "Where" variable was generated using the "Place" text field together with the "Area" and "Location" fields. "Cir_collapse" (circumstances for the collapse) was created using the "Breakdown" as well as the incident description text field, which could include factors such as being thrown from the ATV, falling off the ATV, rolling/tipping/flipping the ATV, colliding with or being towed by the ATV, equipment malfunctioning, or falling through ice. The "Weekend" variable was created from the "Day" of the week field and the "Season" variable was created from the "MONTH" variable. "OH_drugs" was created using the incident description and indicates if the patient was intoxicated with drugs or alcohol.

The "ATV Seat Position" variable replaces the "Vehicle Seat Position" variable. The "ATV Seat Position" variable is more complete since it includes values such as "single driver," unlike the "Vehicle Seat Position" field, which is often left blank when there was only a single driver. The new "ATV Seat Position" variable is more relevant to ATVs because it has codes for when passengers sit in front of the handlebars or on the back of the ATV in atypical seating positions. The "ATV Seat Position" field was further populated using the "WH" (what happened) text field and includes the driver, front passenger, rear passenger, being towed, pedestrian and other vehicle positions.

The "Hit" variable is relevant to ATV injuries because it explains the type of impact that occurred and includes hitting the ground/surface, fixed objects, people, another ATV, people on another ATV, other more specific objects, and a combination of other passengers and the ground. "Hit" was created using the "mf1", "mf2" and text information.

The "Helmet" field was created to replace the "Safety Device" field since this was typically the piece of protective equipment used on ATVs. The "Helmet" field has a code to represent cases where helmet-use is unspecified, although it is likely that there was no helmet used when the field is left blank.

The "Rural" field was created using the postal code of the patient and includes codes for city, rural and unspecified; however, this field may be misleading because the postal code refers to the patient's residence even though the patient may live somewhere other than where the ATV was being used.

The "Severity" output field was originally called "Disposition" and had 10 possible values as can be seen in Appendix D. The "Severity" output was reduced to two higher-level outcomes: one, non-admitted to hospital and two, admitted/fatal. These two outcomes were chosen to represent the outcome based on a frequency analysis that showed 64% of ATV injuries result in non-severe injuries and 36% result in severe injuries. Compared to other types of injuries, ATV injuries have a very high percentage of severe injuries, prompting further investigation based on the outcome [1].

Each case was examined, one by one, in collaboration with Health Canada, to remove cases that were not ATV-related but had been grouped with ATV cases while selecting ATV cases from the larger original CHIRPP database. Variables missing greater than 20% data were removed as has been done in past work by MIRG [29].

In the variables where there was less than 1% missing values, the records containing the missing values were removed. The "Industry" and "Occupation" variables have 99% missing values; these variables were removed due to the high amount of missing data. It is natural for the CHIRPP database to have missing values for these variables since the data is mainly from children who usually do not have occupations or work in industry.

The "Hour" variable has 546 missing values and these missing values were imputed using SPSS's "Replace Missing Value" function, which replaces the missing values with the series mean function. The "Ethnicity" variable was also removed due to its high percentage of missing values and because of a recommendation from the Director of Plan-it Safe at the Children's Hospital of Eastern Ontario, Morag Mackay. This recommendation was made because this variable does not represent ethnicity as much as it does language since 47.1% of the values refer to English and 13.5% refer to French speaking patients.

The final variables used in this work and how they were encoded are described in Table 4.2. This dataset consists of 2927 patient records with 18 input fields and 1 output field. For a more detailed description of the variables please refer to [5, 21].

Table 4.2: ATV Variables and Contents

NODE	Variable	Definition	Codification
INPUT	SEX	sex of patient	1=male, 2=female
	AGEGRP	age group	1 = < 1 yrs 2 = 1 to <2 yrs 3 = 2-4 4 = 5-9 5 = 10-14 6 = 15-19 7 >= 20
	HOUR	hour of injury in the day	1-24

	WEEKEND	weekend of injury	1=weekend, 0=weekday weekend =Friday at 6p.m-Sunday 12a.m
	SEASON		1=spring, 2=summer, 3=fall, 4=winter spring=March 21-June 20 summer=June 21-September 20, fall=September 21- December 20, winter= December 21-March 20,
	YEAR	year of the injury	1990-2004
	JOBREL	job related injury	1= yes, 0=no
	MECHANISM	mechanism of injury	11-99 mechanical, chemical, thermal, electrical, radiation, asphyxiation, other
	FOLLOW-UP	follow-up flag	1=follow-up refused, 0=follow-up allowed the patient or patient's guardian allowed CHIRPP to contact them at a later date to clarify or gather further information
	NI1	nature of injury, i.e. the type of injury	10-99 superficial, open wound, fracture, dislocation, sprain/strain, injury to nerve, injury to blood vessel, injury to muscle to muscle/tendon, crushing injury, traumatic amputation, burn/corrosion, frostbite, bite, electrical, eye, dental, injury to internal organ, foreign bodies, minor head injury, concussion, intracranial injury, poisoning or toxic affect, drowning, asphyxia, systemic over-exertion, other specified, multiple, no injury detected, unspecified
	BP1	body part	110-999 head & neck, spine/spinal cord, trunk, shoulder & arm, hip & leg, multiple injuries, systemic injury, unspecified body part
	RURAL	postal code of the patient	City=0, Rural=1, Unspec=3
	OH_ DRUGS	drugs or alcohol use	0=none, 1=drugs/alcohol

	HIT	obstacle that was hit	0=other specified 100=ground/surface 200=ATV 300=fixed object 400=ground/ATV 500=people 600=people/ATV 700=unspecified 800=people/ground
	CIRC_ COLLAPSE	circumstances of the accident	100=fell/thrown from ATV 200=roll/tip/flip 300=collision with fixed structure 400=while on ATV 500=ATV-other vehicle 600=pedestrian 640=on other vehicle 700=being towed 800=malfunction of ATV 900=fell through ice 1000=other specified 1100=unknown
	WHERE	where the injury occurred	100=road/highway 200=field/open area 300=trail/recreation area 400=farm 500=residential area 600=other specified 610=sand/gravel 620=railroad tracks 630=frozen lake 700=unknown 800=woods/bush/forest 900=yard-own home 901=yard-other private home
	HELMET		1=helmet, 2=no helmet, 3=helmet use unspecified
	ATV SEAT POSITION		1=driver 2=front passenger 3=rear passenger 4=being towed 5=pedestrian 6=on other vehicle 10=unspecified
OUTPUT	SEVERITY		0=not admitted, 1=admitted/fatal

4.3 Performance Testing

Residual evaluation of a model tests the model using data that also trained the model. This type of performance testing shows how the model should perform when exposed to new data. Cross validation is a method of evaluation that tests the performance of the model with 'unseen' data by separating the data into training set and test set. One type of cross validation is called 'the holdout method' because it does not include all of the data in the training set; instead, it uses a portion of the data for training the model and the other portion for testing the model. The mean and standard deviation of the test performance results are used to evaluate the model. Another type of cross-validation is k-fold cross validation, which separates the data into k smaller data sets. Each smaller data set is used as the test set and the rest of the (k-1) data is used as the training set for each validation run [39, 40]. The method of evaluation used in this study is a combination of the k-fold cross validation method and the holdout method. The cross-validation method used in this investigation randomly selects two-thirds of the data for the training set and then randomly selects one-third of the data for each of the 30 test sets, which is an evaluation method used in other previous ANN model analyses done by our research group [29]. The ATV database of 2927 patients, 18 input variables and 1 output variable was divided into a training set with two thirds of the data or 2049 patients, and a test set with the remaining one third of the data or 878 patients.

The raw patient data was assumed to follow a normal distribution. A normal linearization was performed on the patient data according to the Gaussian function to scale the numerical inputs to between -1 and +1:

$$F(x) = (1/\sigma\sqrt{2\pi})\, e^{-(x-\mu)^2/2\sigma^2} \qquad (4.1)$$

where:

$x = -3\sigma \rightarrow 3\sigma$,

σ = variation=1/3,

μ=mean.

Data above or below $-3\sigma \rightarrow 3\sigma$ was grouped together with data in the outer ranges.

The output data format is a Boolean value of -1 or +1 where the most frequent case is -1 output value. The data is randomized using a random number generator, with data-analysis software SPSS [41], to assign random values to each case and sort the random cases.

The validation method uses the testing set to measure the performance of possible ANN architectures as well to measure the ability of the ANN to predict outcomes. To improve the generalization ability of the ANN and to claim that the ANN can predict outcomes, future work is necessary to create separate testing sets for finding the optimal ANN architecture and testing the prediction capability of the ANN. One possible cross-validation technique that can be applied in future work is to separate the data into training and testing sets and then further separate the training set into estimation and validation subsets. The estimation subset is then used to train the ANN and the validation subset is used to test the performance of various ANN architectures. This alternative method uses different data sets to find the best performing ANN architecture and to analyze the prediction capability of the ANN [2].

4.4 Performance Measures

The Medical Information-technology Research Group (MIRG) at the University of Ottawa and Carleton University developed an ANN tool based on Matlab. Several modifications and automation were added to the basic tool [42]. The performance measures of this ANN tool are defined in this section. The performance measures include true positive rate (sensitivity), true negative rate (specificity), logarithmic-sensitivity index, correct classification rate (accuracy), average squared error (ASE) and area under the receiver-operating characteristic (ROC) curve. The definition of sensitivity, specificity and correct classification rate (CCR) are:

Sensitivity = True Positive / (True Positive + False Negative)

Specificity = True Negative / (True Negative + False Positive)

Correct Classification Rate = (True Positive + True Negative)/Total Cases

True positive refers to patients with severe injuries whose outcomes were correctly predicted as severe injuries and false positive refers to patients with non-severe injuries whose outcomes were incorrectly predicted as severe injuries. Conversely, true negative refers to patients with non-severe injuries whose outcomes were correctly predicted as non-severe injuries and false negative refers to patients with severe injuries whose outcomes were incorrectly predicted as non-severe injuries. Table 4.3 illustrates the classification of different combinations of predicted and actual outcomes [43].

Table 4.3: Definitions for Predicted and Actual Outcome Pairs

	Actual Negative	**Actual Positive**
Predicted Negative	True Negative	False Negative
Predicted Positive	False Positive	True Positive

The correct classification rate is usually a good indicator of the network's performance, but it can be a misleading indicator for uneven outcome distributions, as it will poorly classify rare outcomes, i.e. less than 15% prevalence [48].

The logarithmic-sensitivity performance index is the stopping criteria used to decide when the network has reached an optimal and stable value. The logarithmic-sensitivity index, created by MIRG, allows the sensitivity and specificity performance indices to be optimized simultaneously. This is a more efficient method of optimizing the ANN because it automates the process of finding equilibrium between high sensitivity and specificity indices. To optimize the sensitivity and specificity at the same time, just adding the two indices together would give the same level of performance for both an ANN with a high sensitivity/low specificity combination and an ANN with a low sensitivity/high specificity combination. An index that achieves a maximum value when the sensitivity and specificity are both equal to one is required. Furthermore, an index that puts heavier weighting on the level of sensitivity to improve the network's ability to predict the more rare outcomes is also required. The equation for the logarithmic-sensitivity index from [45] satisfies these requirements; the weighting on the level of sensitivity can be adjusted through the value of the exponent "N":

$$\text{Logarithmic-Sensitivity Index} = -\,\text{Sensitivity}^{N} \times \log_{10}(1 - \text{Sensitivity} \times \text{Specificity})$$

Ennett compared use of the logarithmic-sensitivity index to manually finding an optimal sensitivity and specificity combination on an ANN model predicting coronary surgery mortality [45]. Ennett found that the manual experiments resulted in a sensitivity of 43.55% and specificity of 93.83% and use of the logarithmic-sensitivity index resulted in a sensitivity of 49.05% and specificity of 93.85%. These results show that the logarithmic-sensitivity index can accurately and efficiently optimize an ANN.

A receiver operating characteristic (ROC) curve is a plot of the true positive rate (sensitivity) versus the false positive rate (1-specficity). The ROC curve is found by varying the threshold value of the outcome, in this case the output threshold is varied between -1 and 1. ROC curves are often used in clinical analysis to determine how accurately a model can differentiate between two outcomes. The area under an ROC curve is comparable to a measure of the probability that the model will correctly predict the outcome [44]. The area under a ROC curve ranges from 0.5 to 1.0, where 1.0 indicates that the model is 100% accurate and 0.5 indicates that the model has the same chance of predicting either outcome. If the area under the ROC curve is 1.0, it will resemble a step function, but if the area under the curve is 0.5 it will be a 45-degree diagonal line [46].

4.5 ANN Software

The Matlab Neural Network Toolbox is used as a base to which many features were added by MIRG. This setup has been used in past applications of ANNs to medical data by MIRG as mentioned previously. The code allows the user to optimize the ANN for specific models, choose the number of hidden nodes (if any) and the number of hidden layers, and enables the user to run test configurations with or without weight elimination.

The MIRG ANN software consists of two main programs. The first program executes the ANN with a constant set of network parameters. It is referred to as a simple ANN because the user must find the optimal values for the network parameters by adjusting each parameter manually.

The second program runs an automated version of the ANN. This program executes the ANN and keeps all but one network parameter at default values while it searches for the value of that parameter that gives the highest ANN performance results. The program repeats this procedure until the value resulting in the highest performance is found for each network parameter. The search for the value resulting in the highest performance for each network parameter is done over pre-defined ranges shown in Table 4.4. The network finds the highest value within each range by using the 'divide and conquer' method. The algorithm searches for the two highest network performance points, calculates their midpoint, and then selects two new maximum points from these points. This is repeated recursively until the network converges upon the network parameter value that gives the maximum network performance [42, 47].

Table 4.4: Network parameter ranges

Network Parameter	Range
learning rate (lr)	[0.000005, 0.005]
learning rate increment (lr_inc)	[1, 1.305]
learning rate decrement (lr_dec)	[1, 0.695]
weight-elimination constant (λ)	[0, 0.0008]
weight-elimination constant increment (λ_inc)	[1, 1.305]
weight-elimination constant decrement(λ_dec)	[1, 0.695]
weight-elimination scale (w_0)	[0.001, 1]
momentum (α)	[0, 0.99]
error ratio (err_ratio)	[1.001, 1.04]

The manual ANN is a much more time consuming and labor intensive method of finding optimal network parameters. Each parameter must be changed one at a time since changing one parameter can affect other parameters; in other words, the user must find the best combination of optimal network parameters. In a comparison of the manual and automated ANN programs, they resulted in a set of similar optimal network parameters. Thus, the automated ANN is an effective and more efficient method of finding optimal network parameter [42, 47].

4.6 Network Parameter Selection

The automated ANN finds the optimal value for each particular network parameter while the rest of the network parameters are kept at a constant value. In previous applications by MIRG, each set of performance values for each network parameter was manually recorded and the performance of each network parameter was compared in a spreadsheet. The highest performing network parameter was chosen to replace its previous value in the ANN. This process was repeated until the ANN no longer found network parameters that improved ANN performance. Reprogramming of the ANN was carried out to automate this entire process so that the ANN finds a complete set of optimal network parameter values.

The complete process of network parameter selection is described in the following steps.

1. The automated ANN is given a set of default network parameters that are found using the simple ANN.
2. The automated ANN finds the value, in a pre-defined range of values, for each network parameter that gives the highest performance results.
3. The set of performance values for the network parameters are compared to each other and only the highest performing stable parameter value is selected.
4. The highest performing stable network parameter value is used as the default value for the next execution of the automated ANN.
5. Steps 1) to 4) are automatically repeated until the ANN no longer finds values in the network parameter ranges that increase the performance of the ANN.

Steps 3 and 4, the selection of new default network parameters, involve more than choosing a parameter resulting in high network performance. Some network parameters may result in unstable networks or over-fitting of the ANN. The new ANN program studies the performance graphs of logarithmic-sensitivity for each network parameter across epoch runs. Improper learning occurs when the performance graph has a sharp learning curve, has over-fitting or an unstable ANN, which is identified by a learning curve with numerous epochs of rapid steep edges. Performance parameters that result in graphs that show over-fitting or instability are rejected. The final result of the program is a set of stable graphs at the highest performance index for each network parameter.

4.7 ANN Stopping Criteria

Ideally, the automated ANN runs until the performance indicators are consistent and dependable. The manual ANN, is run for 3000 training epochs, which has been proven to be more than enough running time [48]. The automated ANN has a more efficient and faster method of stopping the ANN. The automated ANN records the performance parameter (logarithmic-sensitivity index) after each epoch and terminates execution of the ANN when the performance ceases to improve for 500 epochs [42].

In previous applications by MIRG, the optimal network parameter was recorded at the epoch in which the maximum performance result was achieved over the entire run. This previous algorithm monitored the performance and recorded each maximum point, once a new maximum was found; it continued to search for another maximum for 500 epochs and stopped if no new maximum was found [42]. However, ANN learning may not be consistent and stable at every epoch, especially in the early epochs. In fact, most curves in this study have oscillations in performance during the first few hundred epoch and several test runs have shown that the maximum performance peak varies for tests with the same set of network parameters, but the stabilized performance value does not vary. As a result, the stopping criterion was altered for this study. The new algorithm compares present and past performance at each run and records performance data that is stable for 500 continuous epochs. The optimal network parameter is recorded after the network has stabilized. The previous stopping criterion was causing the ANN to prematurely stop training and was recording the performance at unstable peaks, which could give misleading optimum network parameter selections. The new stopping criterion ensures a stable performance of the ANN prior to establishing the maximum values.

The new stopping criterion avoids stopping at unstable peaks in ANN performance and looks for maximum performance points within stable peaks of performance. The performance of this ANN is such that the stable ANN stopping criteria also satisfies the maximum performance stopping criteria because the learning curve gradually increases and peaks as it becomes stable. A more comprehensive ANN would stop training once a maximum peak is attained during a stable period that may still have oscillations. This is challenging to implement because the variation between a stable oscillating ANN and an unstable or over-fitting ANN can be difficult to differentiate in an automated fashion.

4.8 Variable Reduction Using the Weights Method

Variable reduction is done once the optimal network parameters and network configuration are found. The contribution of each input variable in predicting severity can be found by examining the connection weights of the trained injury severity model using the 'Weights Method' [49]. When the ANN architecture includes a hidden layer, the first step in partitioning the connection weights involves performing a computation for each hidden node.

Step 1)

This is accomplished by finding the products P_{ij} of the absolute values of the hidden-to-output node connections and the input-to-hidden node connections for each hidden node.

$$P_{ij} = (|W_{ih}|)(|W_{ho}|) \tag{4.2}$$

Step 2)

The second step is to use the P_{ij} products to compute Q_{ij} as described by the following algorithm from [50].

For h=1 to the number of hidden nodes

For i=1 to the number of input nodes

$$Q_{hi} = \frac{P_{hi}}{\sum_{i=1}^{number\_inputs} P_{hi}} \quad (4.3)$$

where 'h' refers to the hidden nodes and 'i' refers to the input nodes.

Step 3)

The third step involves computing a sum for each input using the Q_{ij} products to compute S_j.

For i=1 to the number of input nodes:

$$S_i = \sum_{h=1}^{number\_hidden} Q_{ih} \quad (4.4)$$

Step 4)

The last step consists of dividing each of the computed sums by the total of the sums to calculate the relative importance, R_i, for each input variable i:

$$R_i = \frac{S_i}{S_{total}} \tag{4.5}$$

If there are no hidden nodes or layers, the weights on the connections departing each input node are summed and the relative importance for each input variable is then calculated.

5 Simulations and Results

5.1 Frequency Analysis of ATV Database

A frequency analysis is performed in this section to determine if any conclusions can be made concerning which variables affect injury severity. The injury cases are split into non-severe and severe and a frequency analysis is done on each variable (e.g. Helmet-use). Presumably, if the variable's fields (e.g. Helmet used, Helmet not used, etc.) change frequency when comparing the non-severe cases to severe cases, it would suggest that the variable has some effect on injury severity – and could be used as a predictor of severity.

5.1.1 Gender

The data in Table 5.1 and Figure 5.1 illustrate that there is a 3.3% increase for males when moving to severe injuries. This is a small increase and could be due to the deviation from small sample size. Note that there are a greater number of ATV injuries for males than for females; however, this could just be an indication of the greater number of male ATV riders.

Table 5.1: Frequency of parameter "sex" from non-severe to severe injuries

Group (Code)	% of All Non-Severe Injuries	% of All Severe Injuries	Change
Male (1)	73.4	76.8	3.3
Female (2)	26.6	23.2	-3.3

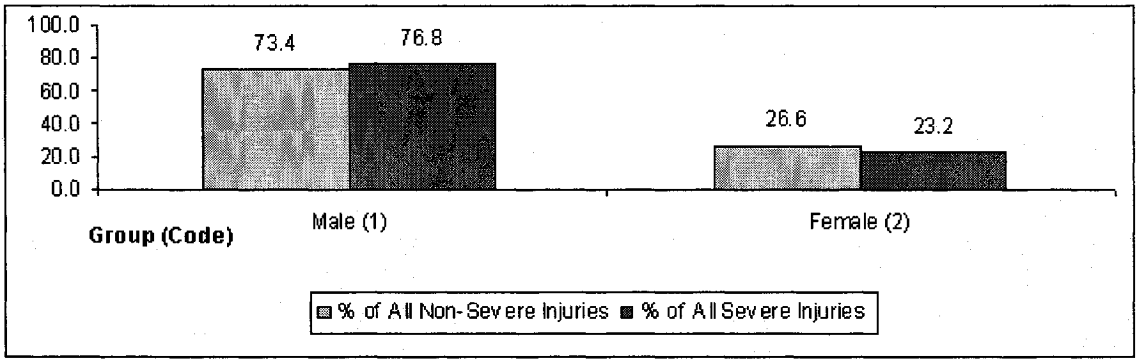


Figure 5.1: Frequency of parameter "sex" by group and severity

5.1.2 Age Group

The data in Table 5.2 and Figure 5.2 show the greatest increase is found in the 5 to 9 age group and the greatest decrease is found in the 20 plus age group. Note that the rate of all ATV injuries increases and peaks in the 10 to 14 age group and stays above 20% for the 15 plus age groups.

Table 5.2: Frequency of parameter "age group" from non-severe to severe injuries

Group (Code)	% of All Non-Severe Injuries	% of All Severe Injuries	Change
<1 yr (1)	0.1	0.1	0.0
1 yr (2)	0.2	0.3	0.1
2-4 yr (3)	3.2	3.8	0.6
5-9 yr (4)	9.1	12.2	3.1
10-14 yr (5)	36.1	34.6	-1.6
15-19 yr (6)	22.8	22.8	0.0
20+ yr (7)	28.5	26.3	-2.2

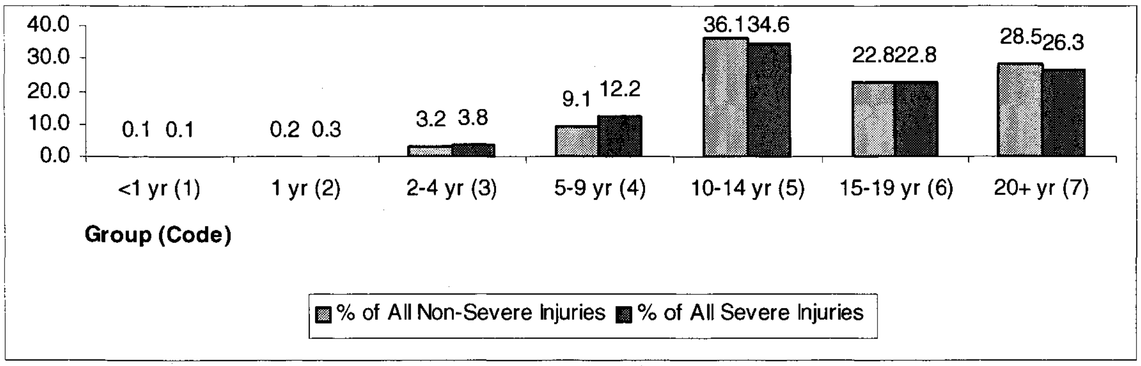


Figure 5.2: Frequency of parameter "age" by group and severity

5.1.3 Job-Related Group

Table 5.3 shows a minuscule change between severe and non-severe injuries for job-related injuries. However, since less than 1% of ATV injuries are job-related, it is difficult to obtain any information due to the lack of job-related ATV injuries.

Table 5.3: Frequency of parameter "job-related" from non-severe to severe injuries

Group (Code)	% of All Non-Severe Injuries	% of All Severe Injuries	Change
No (0)	99.3	99.4	0.1
Yes (1)	0.7	0.6	-0.1

5.1.4 Mechanism Group

The largest increase in severity for the mechanism of ATV injury occurs for the "contact with a moving item" field at 4.2%, followed by "contact with an unknown motion item", and the largest decrease occurs for the "over-extension of a body part" field at 2.9%, followed by "contact with a still item." The frequency analysis for mechanism group is shown in Table 5.4 and Figure 5.3.

Table 5.4: Frequency of parameter "mechanism" from non-severe to severe injuries

Code	% of All Non-Severe Injuries	% of All Severe Injuries	Change
Contact with still item (11)	66.8	65.0	-1.8
Contact with moving item (12)	17.2	21.4	4.2
Contact w/ unkwn motion item (13)	1.1	4.0	2.9
Cut/Tear/Graze (14)	0.4	0.1	-0.3
Pinch/Crush (15)	8.7	7.6	-1.2
Puncture (16)	0.1	0.0	-0.1
Foreign body (18)	0.3	0.0	-0.3
Over-extension of body part (19)	3.7	0.8	-2.9
Punctured/lacerated/abraded (38)	0.5	0.7	0.2
Contact with hot objects (51)	0.9	0.4	-0.5
Contact with open fire/flame (52)	0.1	0.2	0.1
Exposure to cold/frostbite (55)	0.1	0.0	-0.1
Drowned/Nearly drowned (81)	0.1	0.0	-0.1
Multiple mechanisms (95)	0.1	0.0	-0.1

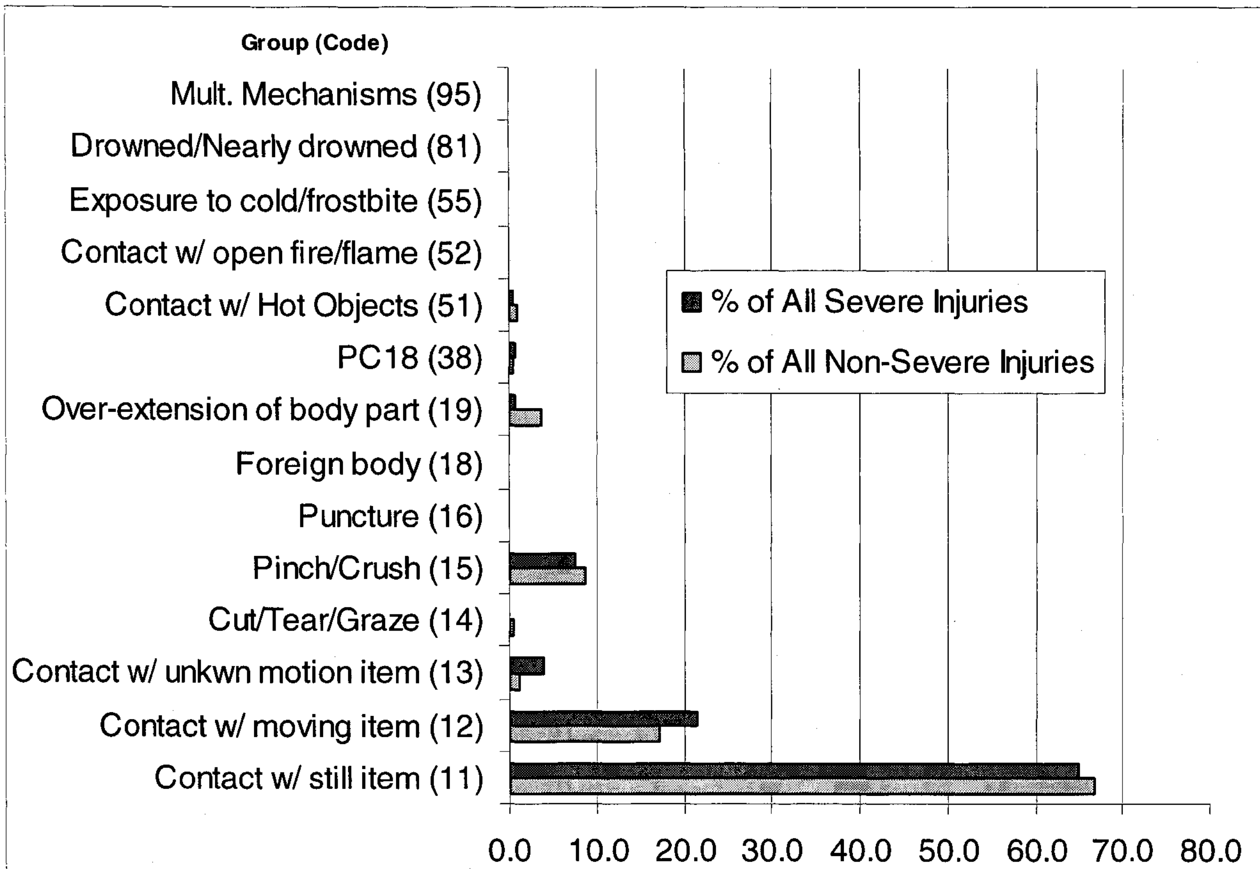


Figure 5.3: Frequency of parameter "mechanism" by group and severity

5.1.5 Follow-Up Group

There is a large increase in the severity of injury for the follow-up group as shown in Table 5.5, which would make this variable a good predictor of the outcome. However, the follow-up variable itself is not helpful in predicting the severity of an injury since the follow-up response occurs after the injury. The reason for the decrease of follow-ups permitted may be that the physician who does not have the authority to permit a follow-up to the patient or the guardian may fill out the accident forms for very severe injuries.

Table 5.5: Frequency of parameter "follow-up" from non-severe to severe injuries

Group (Code)	% of All Non-Severe Injuries	% of All Severe Injuries	Change
Permitted (0)	58.8	25.8	-33.1
Refused (1)	41.2	74.2	33.1

5.1.6 Nature of Injury Group

The nature of injury shows considerable changes in severity for the fields with the most injury cases. If it can be conclusively proven that a certain type of injury leads to higher severity then preventing that type of injury would be beneficial. For example from Table 5.6 and Figure 5.4, there is a much higher rate of intracranial injury in severe injuries (5.5% severe vs. 0.1% non-severe).

Table 5.6: Frequency of parameter "nature of injury" from non-severe to severe injuries

Group (Code)	% of All Non-Severe Injuries	% of All Severe Injuries	Change
Superficial (10)	25.2	1.8	-23.4
Open wound (11)	10.9	3.9	-7.0
Fracture (12)	32.8	60.4	27.6
Dislocation (13)	1.5	1.5	0.0
Sprain/Strain (14)	10.7	0.7	-10.0
Nerve (15)	0.1	1.0	0.9
Blood vessel (16)	0.0	0.4	0.4
Muscle(17)	1.6	0.6	-1.0
Crush (18)	1.0	0.4	-0.6
Amputation (19)	0.2	0.2	0.0
Burn (20)	1.1	0.7	-0.4
Frostbite (21)	0.1	0.0	-0.1
Eye (24)	0.7	0.7	-0.1
Dental (25)	0.5	0.1	-0.4
Internal (26)	0.3	5.9	5.7
Other (27)	6.0	0.5	-5.6
Foreign body eye (31)	0.2	0.0	-0.2
Oth foreign body (36)	0.1	0.0	-0.1
Minor head (41)	4.1	3.0	-1.1
Concussion (42)	2.0	5.4	3.4
Intracranial (43)	0.1	5.5	5.4
Drown (51)	0.1	0.0	-0.1
Asphyxia (52)	0.1	0.2	0.1
Over-exertion (53)	0.1	0.0	-0.1
Multiple Injuries (60)	0.2	7.3	7.1
None (70)	0.6	0.0	-0.6

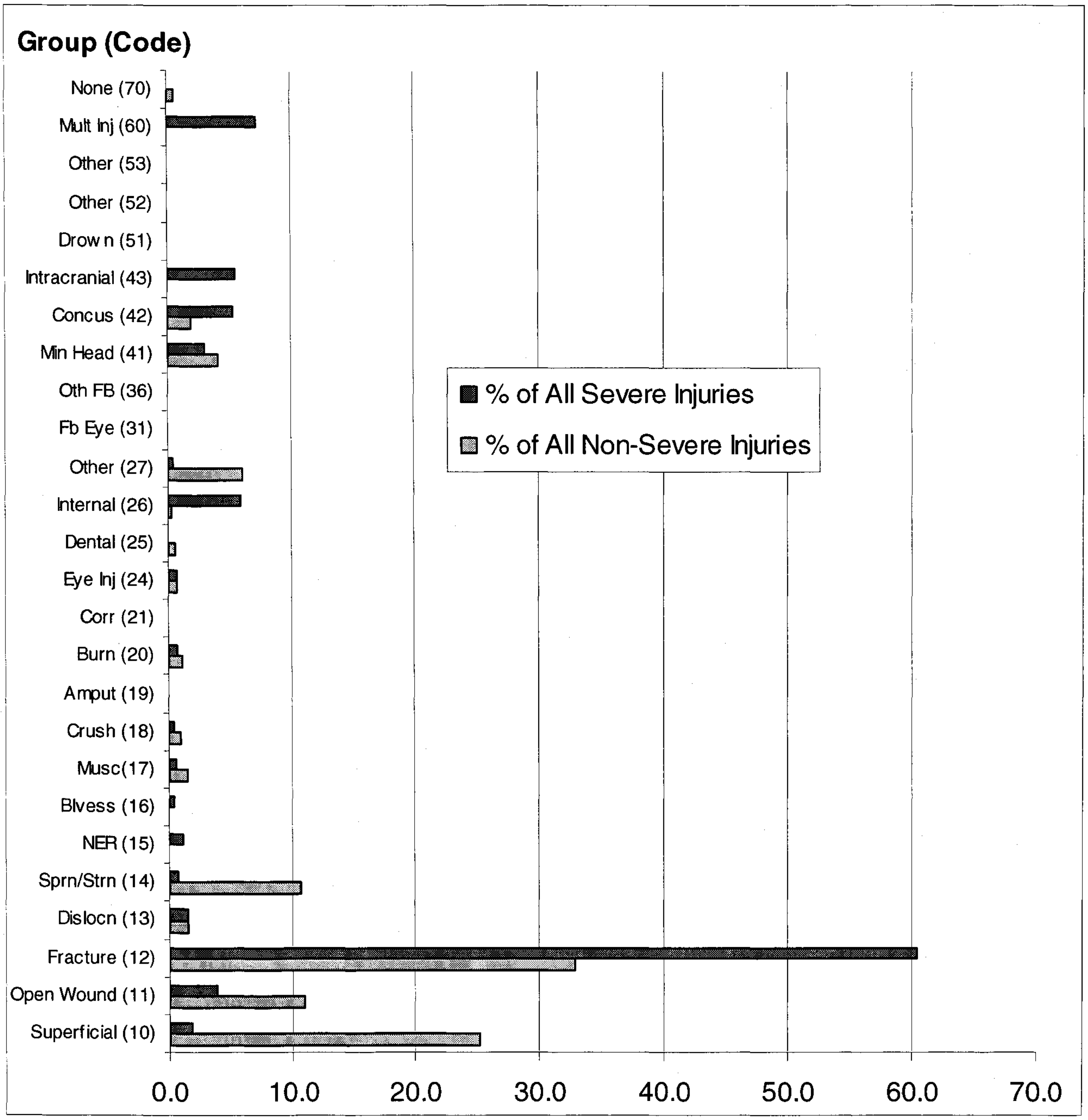


Figure 5.4: Frequency of parameter "nature of injury" by group and severity

5.1.7 Body Part Group

The body part variable shows in Figure 5.5 that the greatest changes in injury severity are for lower extremities at 7.5%, head injuries at 7.1%, multiple injuries at 6.9%, followed by spine/cord injuries at 5.9%.

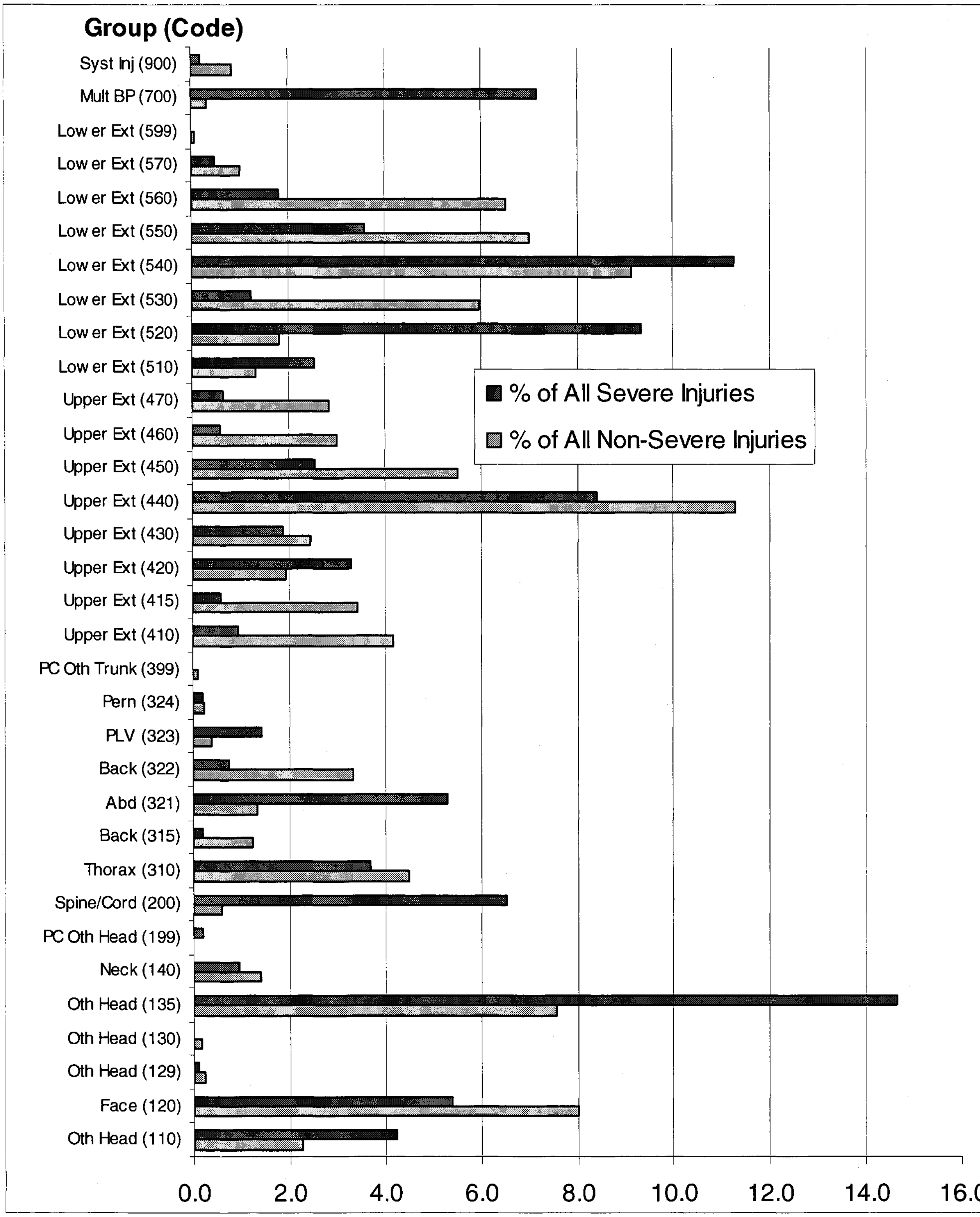


Figure 5.5: Frequency of parameter "body part" by group and severity

5.1.8 Intent Group

There are small changes in severity for the intent variable, see Table 5.7. Note that most ATV injuries are unintentional, which would make it difficult to draw any conclusions about intentional ATV injuries.

Table 5.7: Frequency of parameter "intent" from non-severe to severe injuries

Code	% of All Non-Severe Injuries	% of All Severe Injuries	Change
Unintentional (10)	99.7	99.5	-0.2
Self-Inflicted (11)	0.0	0.1	0.1
Maltreated parent (15)	0.2	0.2	0.0
Maltreated spouse (17)	0.0	0.1	0.1
Undetermined (18)	0.1	0.1	0.0

5.1.9 Year Group

The year variable shows in Figure 5.6 that the amount of ATV injuries is on the rise almost every year with the exception of the year 2003. The year fields do not show any major changes in the severity.

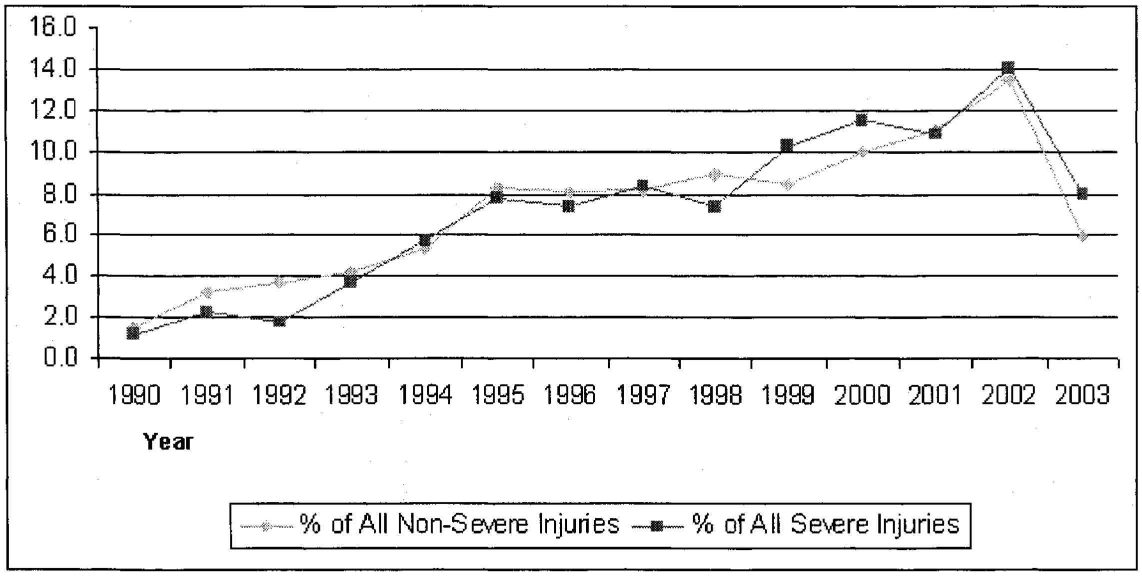


Figure 5.6: Frequency of parameter "year" by group and severity

5.1.10 Rural Group

The rural group shows an increase of 11.6% in severity for "rural" injuries in Table 5.8 and Figure 5.7. However, the rural variable may be misleading because this variable is based on the patient's postal code, which may not correspond to the location where the injury occurred.

Table 5.8: Frequency of parameter "rural" from non-severe to severe injuries

Group (Code)	% of All Non-Severe Injuries	% of All Severe Injuries	Change
City (0)	74.4	63.6	-10.9
Rural (1)	23.3	34.8	11.6
Unknown (3)	2.3	1.6	-0.7

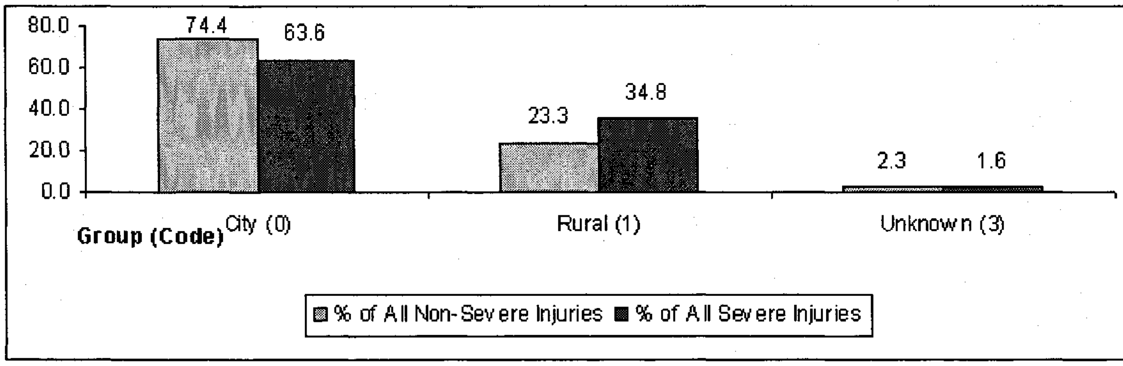


Figure 5.7: Frequency of parameter "rural" by group and severity

5.1.11 Season Group

The season variable does not show any sizeable changes in severity of injury for any particular field in Figure 5.8. Note that the majority of ATV injuries occur in the fall.

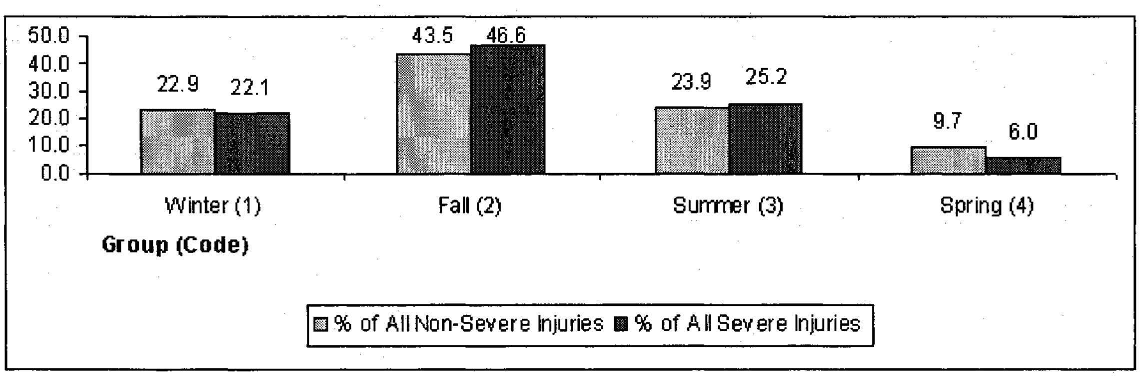


Figure 5.8: Frequency of parameter "season" by group and severity

5.1.12 Weekend Group

The weekend variable does not show any large changes in severity of injury on the weekends in Figure 5.9. The amount of ATV injuries increases on the weekend and this may be due to more people riding ATVs on the weekend.

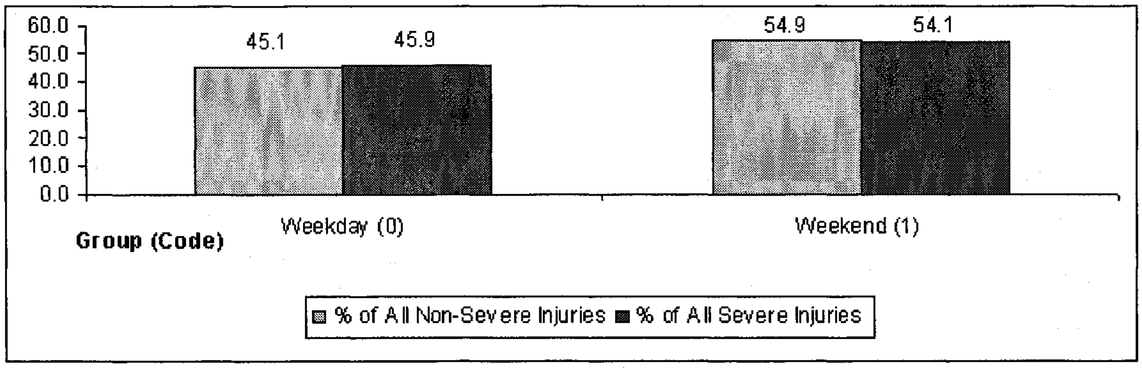


Figure 5.9: Frequency of parameter "weekend" by group and severity

5.1.13 Drugs Group

The "drugs" variable shows an increase of 1.3% in injury severity with drugs/alcohol in . Most injuries do not involve drugs/alcohol use (Figure 5.10).

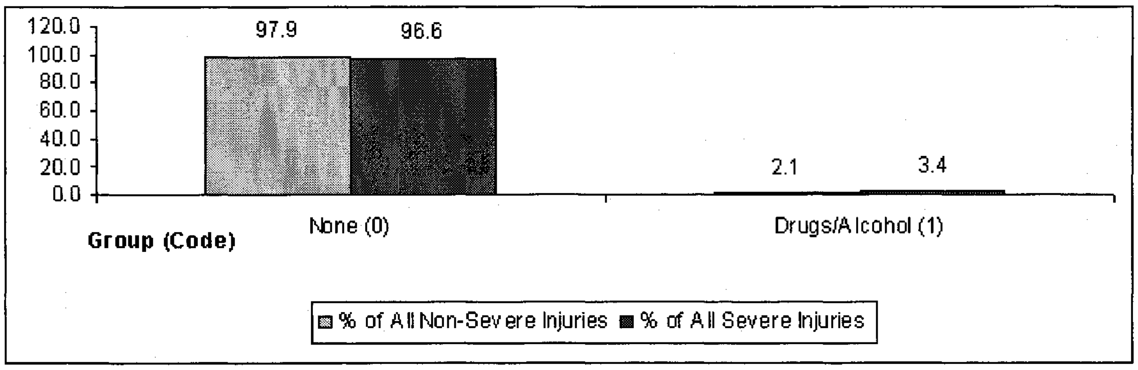


Figure 5.10: Frequency of parameter "drugs" by group and severity

5.1.14 Object Hit Group

The greatest change in severity for the "object hit" variable occurs when the object hit is another ATV at –5.9% and when the object hit is the ground/surface at 3.4% as shown in Figure 5.11.

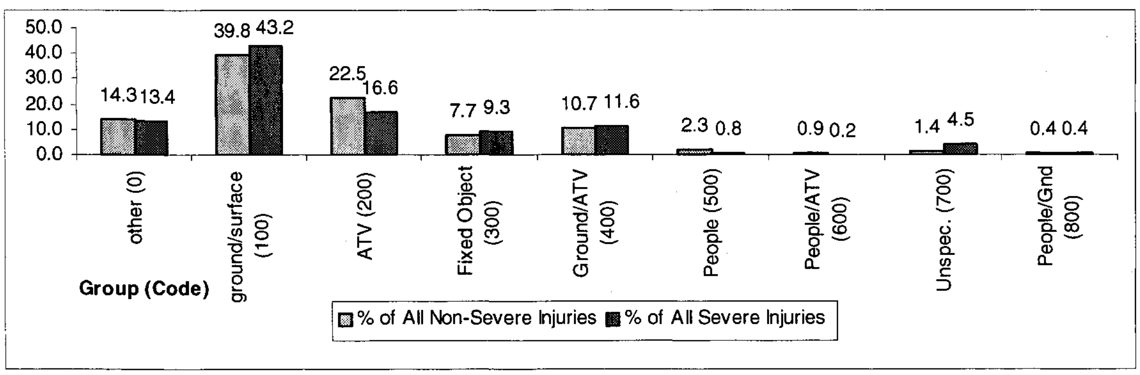


Figure 5.11: Frequency of parameter "object hit" by group and severity

5.1.15 Circumstances of Collapse Group

There is a large change in severity for the "circumstances of the collapse" variable in the "while on an ATV" field of –14.7% and the "ATV with another vehicle" accident field of 4% as shown in Figure 5.12. The former could indicate that staying on the ATV is conducive to non-severe injuries.

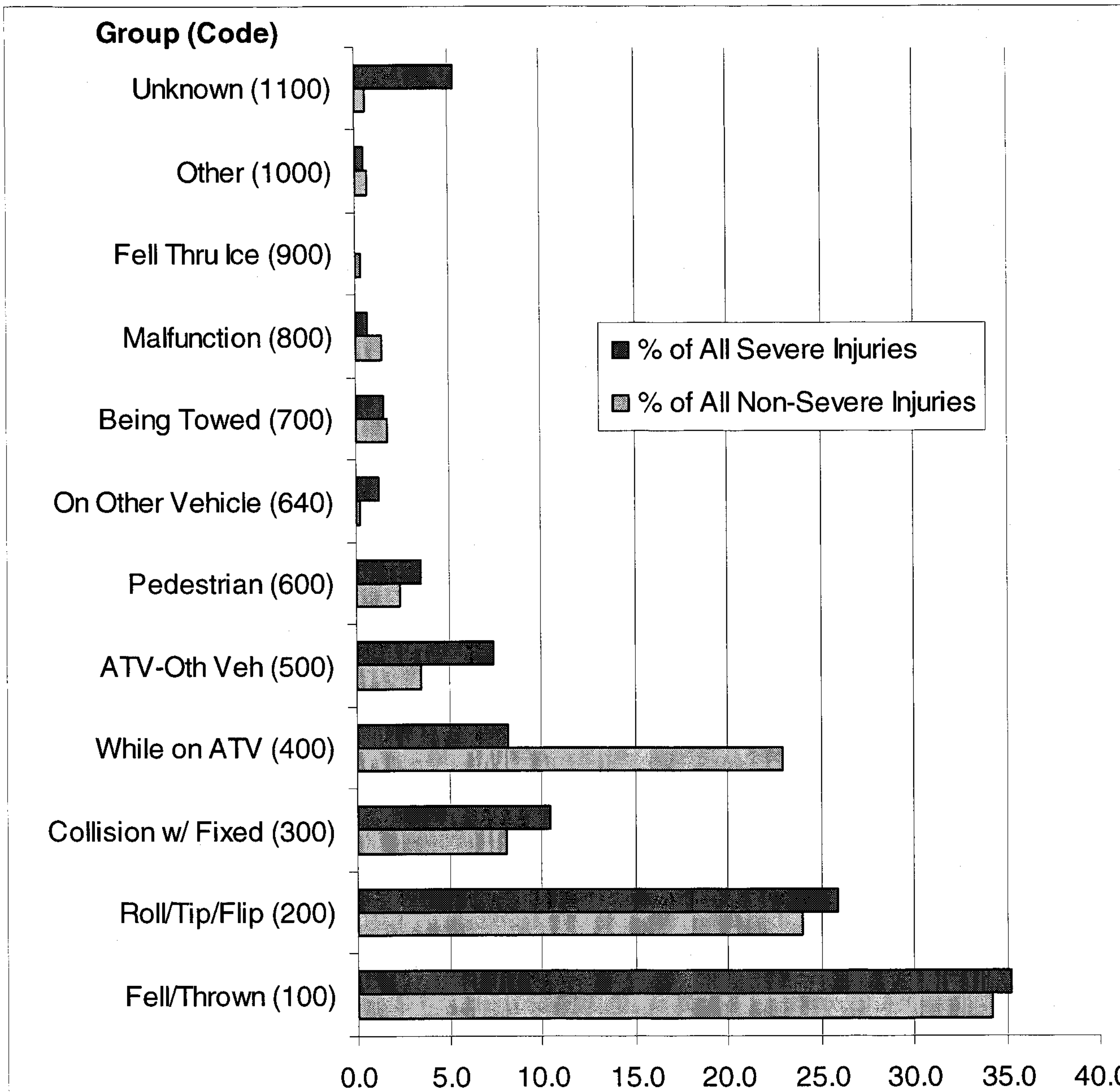


Figure 5.12: Frequency of parameter "circumstances of collapse" by group and severity

5.1.16 Helmet Use Group

The largest change in the helmet variable fields is a decrease of 8.7% in the amount of severe injuries when a helmet is used as shown in Table 5.9 and Figure 5.13. This fact can probably be taken to mean that helmet use can effectively decrease injury severity in an accident. The variable data is somewhat confused because of the large amount of cases involving unspecified helmet-use. However for the most part, this can be taken to mean that a helmet was not used. Supporting this assumption is the fact that the "unspecified" field tracks severity similarly to the "no helmet" field.

Table 5.9: Frequency of parameter "helmet" from non-severe to severe injuries

Group (Code)	% of All Non-Severe Injuries	% of All Severe Injuries	Change
Used (1)	36.5	27.8	-8.7
No Helmet (2)	11.8	15.1	3.3
Unspecified (3)	51.7	57.1	5.4

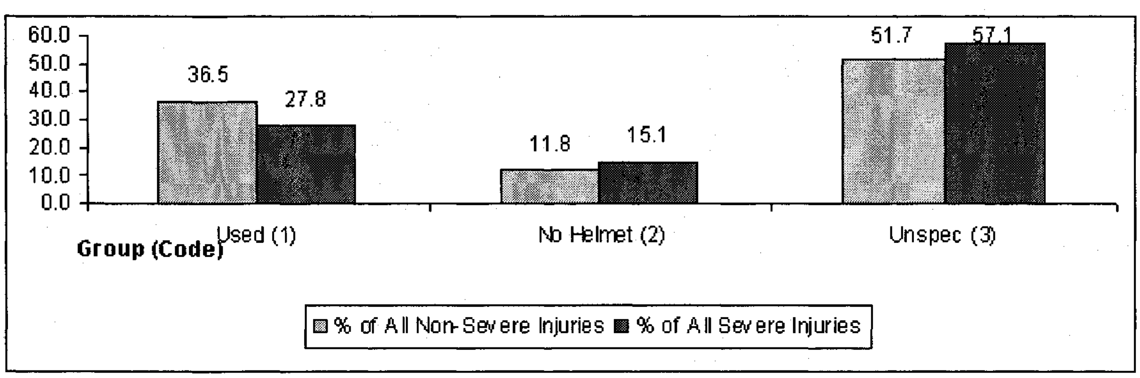


Figure 5.13: Frequency of parameter "helmet" by group and severity

5.1.17 Seat Position Group

The ATV seating position shows in Table 5.10 and Figure 5.14 an increase in the severity of injuries for the driver seat position and an increase in the unspecified driver seat position. There are no substantial changes in the severity of injury for the other fields; however, this could be due to the lower amounts of injuries represented in these fields.

Table 5.10: Frequency of parameter "seat position" from non-severe to severe injuries

Group (Code)	% of All Non-Severe Injuries	% of All Severe Injuries	Change
Driver (1)	44.2	52.6	8.4
Front Passenger (2)	1.6	1.7	0.1
Rear Passenger (3)	20.9	18.2	-2.7
Being Towed (4)	1.7	1.5	-0.2
Pedestrian (5)	2.4	3.5	1.1
On other vehicle (6)	0.2	1.2	1.0
Unspecified (10)	29.0	21.2	-7.8

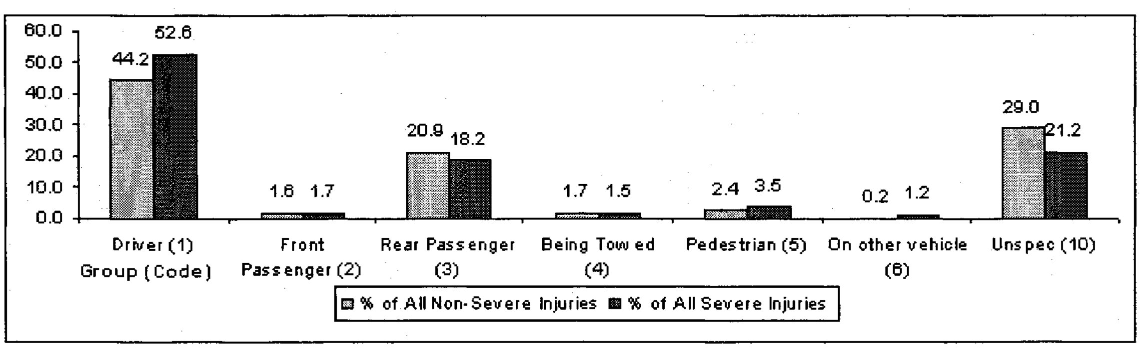


Figure 5.14: Frequency of parameter "position" by group and severity

5.1.18 Hour of Day Group

There are no large differences throughout the day in injury severity other than a small decrease in the early evening and increase in the late evening as shown in Figure 5.15. Note that the amount of overall injuries increase in the early evening, which could be due to an increase in ATV riding after work.

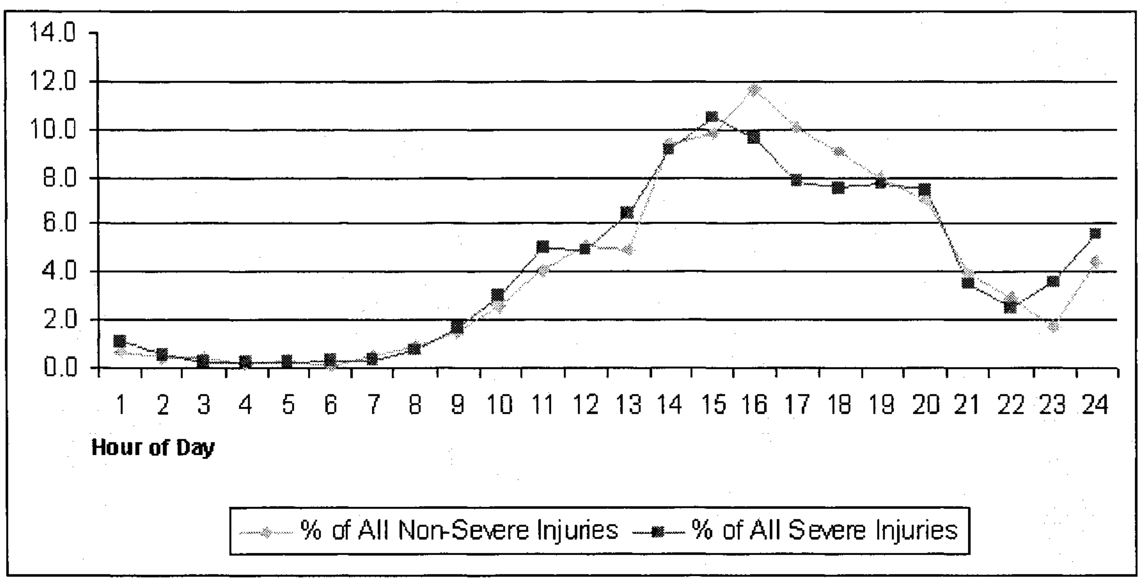


Figure 5.15: Frequency of parameter "hour of day" by group and severity

5.2 ANN Simulations

The ANN is optimized and adapted to model the severity outcome for a set of ATV injury data. The MIRG ANN program is used to find the optimal network parameters, architecture and weights of the final ANN model. The first set of ANN implementations is carried out to find the ANN architecture, i.e. the number of nodes in the ANN and the second set of tests are done to find the optimal network parameters for the ANN. The third set of tests is done to extract and analyze the weights once the ANN implementation is completed and optimized.

These tests and their aims are:

1. Set-A: to find the optimal ANN architecture;

2. Set-B: to find the optimal network parameters;

3. Set-C: extract and analyze the ANN weights.

5.2.1 Optimal Performance and Hidden Layers

The process of finding optimal network parameters begins with finding a set of default network parameters. The initial ANN network parameters are set up using the manual two-layer ANN program. The initial network parameters in Table 5.11 below are chosen using trial and error such that performance graphs of the ANN are stable.

Past work by MIRG has been carried out to finding the impact on ANN performance when the network parameter values are optimized and adjusted [47]. This investigation focused on the use of ANNs for estimating medical outcomes and found that the optimal learning rate increment and decrement and the weight-decay constant increment and decrement parameters all had a value of one. The increment and decrement parameters are multiplied by their corresponding network parameters, i.e. learning rate and weight decay. Multiplying these parameters by one result in no change in the network parameters; therefore, the increment and decrement parameters had no impact.

This work also explored the affects of changing the network parameters on the performance of the ANN. It found that changes to the weight-decay constant and learning rate decrement had little effect on ANN performance; however, changes to the momentum, error ratio, learning rate and learning rate increment are more sensitive to ANN performance.

The default learning rate increment and decrement and the weight-decay constant increment and decrement parameters found by this work agree with MIRG's findings as they are also very close to the value of one. Furthermore, the pre-defined ranges for the network parameters, shown earlier in Table 4.4, were set to a smaller range of values for network parameters, which MIRG had shown to have little impact on ANN performance.

Table 5.11: Default ANN network parameters

Learn rate	**learn rate inc.**	**learn rate dec.**	**weight - elimination constant (λ)**	**λ_inc.**	**λ_dec.**	**weight - elimination scale (w_0)**	**momentum**	**error ratio**
0.0002	1.001	1.001	0.0001	1	1.001	0.001	0.4	1.001

The number of hidden layers needed in an ANN was discussed in Section 3. In general, an ANN with no hidden layers can model linearly separable input variables, whereas multi-layer ANNs (i.e. ANNs with more than one hidden layer) can model more complex and nonlinear problems [2]. The common opinion of researchers is that problems that are more complex require an increase in the number of hidden layers [33]. However, other researchers have shown that having one hidden layer is sufficient for any problem [48, 51].

The greater the number of hidden nodes in the network, the greater time it takes to train the network. In addition, too many hidden nodes can result in over-fitting of the ANN, i.e. the ANN memorizes the training dataset and its ability to generalize test data decreases. There are several methods for choosing the number of hidden nodes used by researchers. Many researchers choose 50% or 75% of the input nodes as the number of hidden nodes [1, 3]. Another approach is to use

2n+1 hidden nodes, where n is the number of input nodes. However, each network has its own characteristics and thus its own optimal number of hidden nodes [51].

Table 5.12 shows the optimal network parameters for ANN architectures with hidden nodes comprising 50%, 75% of the input nodes and (2n+1) input nodes using the ATV CHIRPP database described in Table 4.2.

Table 5.12: Values of network parameters for different numbers of hidden nodes at optimal performance

	number of hidden nodes						
	0	**1**	**2**	**3**	**9 (50%)**	**14 (75%)**	**37 (2n+1)**
learn rate	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
learn rate increment	1.001	1.001	1.001	1.001	1.001	1.0404	1.001
learn rate decrement	1.0008	1.001	1.001	1.001	1.001	1.001	0.7978
weight decay (λ)	0.0001	0	0.0001	0.0001	0.0001	0.0001	0
weight decay increment	1.01	1.001	1	1	1.0019	1.0176	1
weight decay decrement	0.9981	1.001	1.001	1.001	1.001	0.9981	1.001
weight scale parameter (w_o)	0.001	0.0099	0.001	0.0089	0.025	0.9901	1.00E-03
momentum	0.285	0.4	0.712	0.173	0.4	0.4	0.712
error ratio	1.001	1.001	1.001	1.001	1.001	1.001	1.001

Table 5.13 shows the logarithmic-sensitivity for each optimal network parameter. The performance graphs are more unstable and over-fitting begins to occur as the number of hidden nodes was increased. Note also that the default network parameter was kept at its original value in Table 5.12 when the ANN was unstable or showed over-fitting in Table 5.13. The highest

logarithmic-sensitivity performance occurred for an ANN architecture that consists of no hidden layers or hidden nodes.

Table 5.13: Logarithmic-sensitivity values for network parameters at optimal performance for various numbers of hidden nodes (and if they are unstable or over-fitting occurs)

	number of hidden nodes						
	0	**1**	**2**	**3**	**9 (50%)**	**14 (75%)**	**37 (2n+1)**
learn rate	unstable	unstable	over-fitting	unstable	unstable	unstable	0.075
learn rate increment	unstable	unstable	0.08	unstable	unstable	unstable	over-fitting
learn rate decrement	0.0896	0.086	unstable	0.074	unstable	0.08	over-fitting
weight decay (λ)	unstable	0.0836	0.08	0.065	0.075	over-fitting	0.071
weight decay increment	0.0896	0.086	unstable	unstable	0.07	over-fitting	0.075
weight decay decrement	0.0896	0.086	0.082	0.071	0.0805	over-fitting	0.075
weight scale parameter (w_o)	unstable	0.086	unstable	0.068	0.064	0.07	0.075
momentum	0.0896	unstable	0.076	unstable	0.073	unstable	0.08
error ratio	unstable	0.086	0.08	0.068	unstable	over-fitting	over-fitting

The performance of the ANN is found using thirty different test dataset combinations. These test datasets are created by randomly selecting 30% of the data from the full ATV dataset. The complete ANN performance results of the thirty test results are available in Table 5.14. The mean and standard deviation ANN performance results for the test sets are shown in Table 5.15.

Table 5.14: ANN performance results of 30 test sets

test set	logarithmic-sensitivity	sensitivity	specificity	CCR (%)	ROC Area	ASE	epoch
1	0.081654	0.42453	0.84286	69.1344	0.7179	0.82167	426
2	0.083436	0.42122	0.86949	71.0706	0.7278	0.79618	375
3	0.080757	0.41379	0.41379	70.7289	0.733	0.78357	521
4	0.068613	0.3913	0.84892	68.1093	0.688	0.80103	1025
5	0.082681	0.43087	0.82892	68.7927	0.7046	0.82637	1043
6	0.095057	0.46061	0.82117	68.5649	0.6987	0.85064	1238
7	0.051963	0.35644	0.8	64.6925	0.6537	0.89724	32
8	0.067158	0.38643	0.85343	67.3121	0.6965	0.87889	270
9	0.081339	0.4513	0.75263	64.6925	0.6484	0.9049	201
10	0.0874	0.43876	0.83844	69.3509	0.7145	0.8253	705
11	0.087161	0.44051	0.83069	69.2483	0.7213	0.8204	207
12	0.095164	0.82124	0.46081	69.1069	0.7176	0.82115	91
13	0.075288	0.4148	0.82353	67.2523	0.6972	0.85733	1386
14	0.089893	0.44575	0.83333	68.8629	0.7108	0.8388	1364
15	0.059793	0.36957	0.84158	67.5399	0.6808	0.86405	48
16	0.068932	0.39871	0.82363	67.3121	0.6787	0.87201	204
17	0.080043	0.42202	0.83848	68.3371	0.6969	0.85816	228
18	0.077318	0.4127	0.84902	69.2483	0.7104	0.82519	1321
19	0.078333	0.41195	0.86071	69.8178	0.7193	0.81336	695
20	0.08915	0.44192	0.84077	69.4973	0.7211	0.81907	831
21	0.079798	0.41503	0.86189	70.615	0.697	0.83498	232
22	0.09127	0.44839	0.83451	69.8178	0.7221	0.79699	579
23	0.098781	0.46372	0.83601	70.1595	0.7206	0.82137	95
24	0.075413	0.4081	0.84919	68.7927	0.7102	0.82891	240
25	0.1005	0.47742	0.80458	68.9066	0.6969	0.84603	121
26	0.078401	0.41096	0.86505	70.327	0.72	0.81071	470

27	0.081247	0.44012	0.78676	65.4897	0.6854	0.8905	1399
28	0.082996	0.42608	0.84828	69.4973	0.7149	0.82625	511
29	0.087732	0.43658	0.84846	0.7206	0.8233	0.8233	378
30	0.069384	0.3913	0.85665	69.8178	0.7083	0.81756	1400
mean	0.080889	0.435737	0.808786	66.42719	0.707863	0.83573	587.8667
std. dev.	0.010794	0.076426	0.102305	12.30327	0.029047	0.030017	460.7235

Table 5.15: Mean and standard deviation ANN performance results for 30 test sets with severity outcome

Outcome	Logarithmic-sensitivity	Sensitivity (%)	Specificity (%)	CCR (%)	ROC Area	CP (%)
Severity	9.14 ± 1.26	44.44 ± 2.79	83.93 ± 1.49	69.67 ± 1.52	0.7191 ± 0.016	64.0

The logarithmic-sensitivity, sensitivity, specificity, ROC and CCR curves for one test run at the optimal network parameters is shown in Figure 5.16 and Figure 5.17.

Figure 5.16: Logarithmic-sensitivity, sensitivity and specificity train and test curves for optimal network parameters

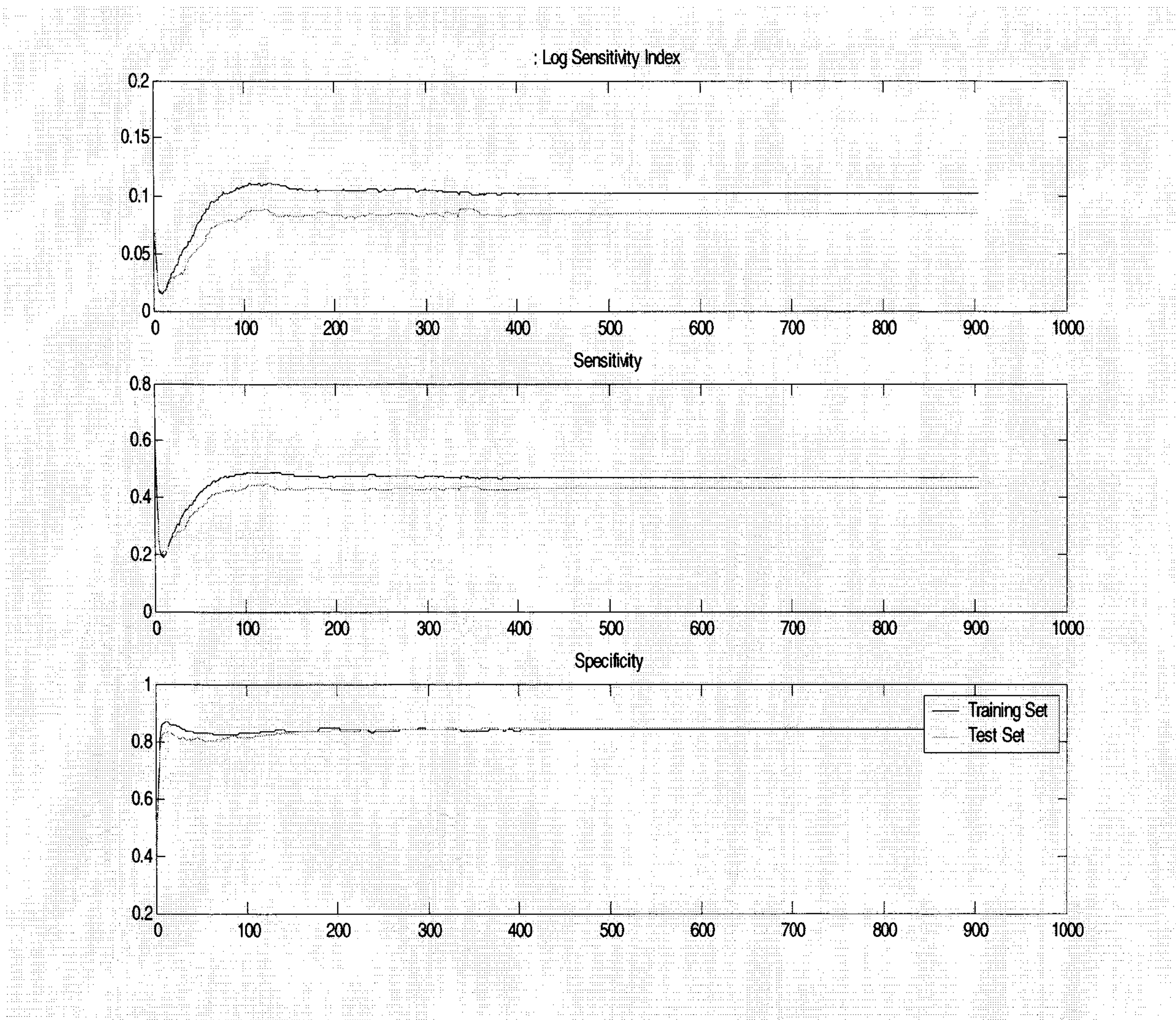
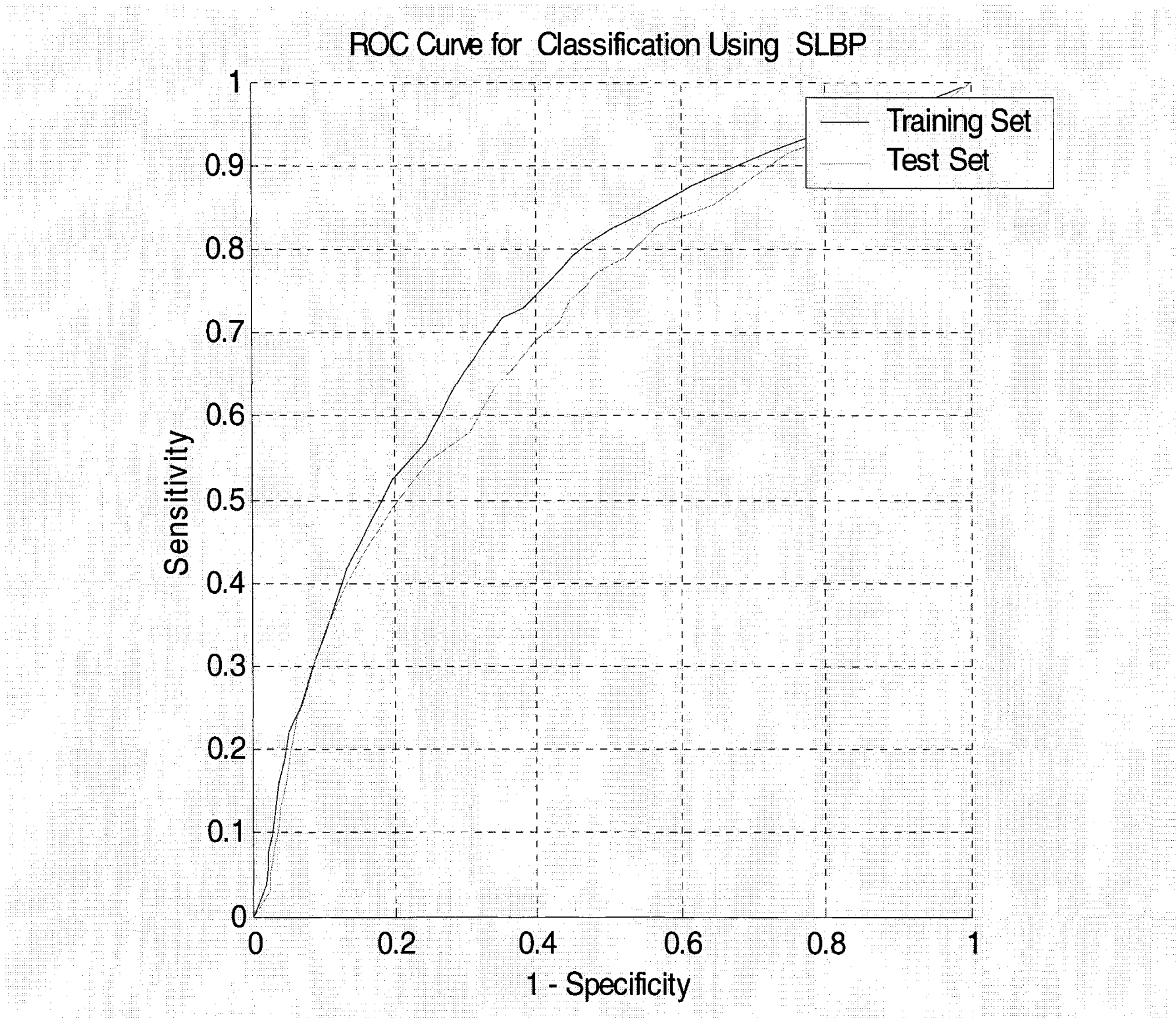


Figure 5.17: ROC graphs for optimal network parameters



The CCR and ASE curves for one test run at the optimal network parameters are shown in Appendix E.

5.3 Input Set Reduction

The weights for the complete set of input variables (shown in Table 5.19, 'Initial Wt') for the ANN severity model, ranked in order from highest to lowest are: follow-up, job-related, nature of injury, drugs, body part, age group, mechanism, ATV seat position, helmet, circumstances of collapse, season, year, hour, sex, rural, hit, where and weekend.

The ANN weights are examined to find the minimum input variable set required to predict the severity outcome for an ANN consisting of 18 input nodes. The input variables with the lowest normalized weights are removed one at a time until ANN performance degrades. At each reduction of the variable set, a new set of optimal network parameters are found for each new ANN. The progression of input reductions is available in Table 5.19 below. Reduction "Initial" has weight values for the ANN consisting of 18 input nodes. Each following reduction removes an input node with the lowest weight value in the previous reduction set.

The first reduction based on weight values removes the "weekend" variable, which is the only variable with weighting of less than 1. The second, third, fourth reductions remove the "where", "season", "drugs", variables at 2.0, 2.0 and 2.9 respectively. The next set of variables' lowest weight is 9.8 for the "hit" variable. The sixth reduction removes the "year" variable with a weight of zero. The next reductions are made even though the lowest weights are all above 10. The seventh and eighth reductions remove the "rural" and "hour" variables at weights of 13.1 and 15.8.

The input variable set is reduced until there is degradation in the performance of the ANN. The removal of the "sex" variable results in a degradation of ANN performance because the logarithmic-sensitivity goes below 0.08 for the first time; therefore, the "sex" variable is kept. The remaining variables ranked in order of highest to lowest are: follow-up, age group, nature of injury, mechanism, helmet, body part, job-related, ATV seat position, circumstances of collapse and sex. The performance before each reduction is presented in Table 5.16.

Table 5.16: Performance results at each input variable reduction step

Reduction (number of input nodes removed)	Logarithmic-sensitivity	Sensitivity (%)	Specificity (%)	CCR (%)	CP (%)
0	0.085	43.1	84.6	69.1	64.0
1	0.088	43.4	85.8	70.0	64.0
2	0.081	41.9	85.5	69.2	64.0
3	0.080	41.3	87.3	70.2	64.0
4	0.084	42.2	87.3	70.5	64.0
5	0.083	42.2	86.6	70.0	64.0
6	0.082	41.6	87.7	70.5	64.0
7	0.082	41.9	86.6	69.9	64.0
8	0.082	41.9	82.2	70.0	64.0
9	0.077	41.0	86.0	69.2	64.0

5.4 Further Reductions

Out of all the injuries, 95.9% of the ATV injuries are not job-related and 4.1% are job-related. This is not surprising since the CHIRPP database is mostly from children's hospitals. The lop-sided nature of the job-related variable may be adding "noise" to the ANN and reducing its ability to classify outcomes. The job-related variable is removed from the input dataset to observe the effect this has on the performance of the ANN; results of this reduction are shown below in Table 5.17. It shows that the removal of the job-related variable results in a minor improvement in ANN performance.

Table 5.17: Performance results with the removal of the job-related variable

Reduction (number of input nodes removed)	Logarithmic-sensitivity	Sensitivity (%)	Specificity (%)	CCR (%)	CP (%)
10	0.090	44.0	85.5	70.0	64.0

The follow-up variable is based on whether the patient agreed to the possibility of being contacted by CHIRPP to clarify data or gather more information; the decision to have a follow-up is made after the accident occurs. Further discussions with epidemiologists at Health Canada support the removal of the job-related variable. The results of this reduction are shown in Table 5.18.

Table 5.18: Performance results with the removal of the follow-up variable

Reduction (number of input nodes removed)	Logarithmic-sensitivity	Sensitivity (%)	Specificity (%)	CCR (%)	CP (%)
11	0.0327	26.6	92.7	68.1	64.0

The remaining variables ranked in order of highest to lowest are: nature of injury, helmet, age group, mechanism, ATV seat position, circumstances of collapse, body part and sex with corresponding normalized weights of 100.0, 99.3, 85.2, 78.2, 47.1, 37.5, 36.6 and 29.8.

Table 5.19: Input node reduction using weight values

Initial	Wt	1	Wt	2	Wt	3	Wt	4	Wt	5	Wt	6	Wt	7	Wt	8	Wt	9	Wt	10	Final Wt
V1	16.5	V1	17.7	V1	17.7	V1	20.1	V1	20.2	V1	0.4	V1	20.1	V1	21.5	V1	21.9	V1	20.0	V1	29.8
V2	33.5	V2	58	V2	58	V2	72.9	V2	71.9	V2	65.4	V2	71.7	V2	82.9	V2	83.4	V2	78.0	V2	85.2
V3	20.7	V3	12.8	V3	12.8	V3	16.9	V3	16.5	V3	0.2	V3	16.4	V3	15.8	V4	29.3	V5	38.3	V5	78.2
V4	54.8	V4	7	V4	7	V4	54.4	V4	44	V4	36.1	V4	70.1	V4	53.9	V5	37.9	V6	100.0	V7	100.0
V5	31.3	V5	35.4	V5	35.4	V5	38.4	V5	39.2	V5	36.6	V5	38.1	V5	37.6	V6	100	V7	51.5	V8	36.6
V6	100	V6	100	V6	100	V6	100	V6	100	V6	100	V6	100	V6	100	V7	49.4	V8	31.8	V16	37.5
V7	49.5	V7	50.1	V7	50.1	V7	50	V7	49.7	V7	47.6	V7	48.9	V7	49.4	V8	30.8	V16	24.3	V17	99.3
V8	35	V8	27.8	V8	27.8	V8	28.8	V8	27.8	V8	25.7	V8	27.5	V8	30.9	V16	24.8	V17	34.7	V18	47.1
V9	21.8	V9	4.2	V9	4.2	V9	22.8	V9	23.9	V9	0	V10	13.1	V16	24.7	V17	33.8	V18	27.2		
V10	13.2	V10	13.1	V10	13.1	V10	13.2	V10	12.9	V10	13.3	V16	24.6	V17	33.6	V18	28.4				
V11	4.5	V11	2.1	V12	2.1	V14	2.9	V15	9.8	V16	25	V17	28.7	V18	28.2						
V12	21.9	V12	22.5	V14	22.5	V15	8.2	V16	21.8	V17	0.9	V18	27.3								
V13	0.1	V14	3.7	V15	3.7	V16	21.9	V17	28.8	V18	25.3										
V14	48.4	V15	8.3	V16	8.3	V17	30.6	V18	27.2												
V15	7.5	V16	21.8	V17	21.8	V18	29.8														
V16	22.2	V17	26.7	V18	26.7																
V17	24.4	V18	27.2																		
V18	28.4																				

*V1: sex, V2: age-group, V3: hour, V4: job-related, V5: mechanism, V6: follow-up, V7: nature of injury, V8: body part, V9: year, V10: rural, V11: where, V12: season, V13: weekend, V14: drugs, V15: hit, V16: circumstance of collapse, V17: helmet, V18: ATV seat position

5.5 Comparison with Bivariate Correlation

A bivariate Spearman correlation is used to demonstrate the relationship between the outcome and the final injury database variables using SPSS (data analysis software). A Spearman correlation is shown in equation (5.1) from [52].

$$r_s = 1 - \frac{6\sum d_i^{\,2}}{n(n^2-1)} \tag{5.1}$$

where 'r_s' is the correlation coefficient, 'd_i' is the difference, 'n' refers to the number of pairs.

The results of the correlation are shown in Table 5.20. Correlation at a confidence level of 0.05 is analogous to a 95% probability and a confidence level of 0.01 to a 99% probability of a high correlation. The correlation of the final input variables to the severity outcome ranked in order from highest to lowest are: nature of injury, ATV seat position, helmet, body part, age, sex, circumstances of the collapse and mechanism. The reduced input variables in the ANN severity model using weights to rank the variables from highest to lowest are: nature of injury, helmet, age group, mechanism, ATV seat position, circumstances of collapse, body part and sex.

Table 5.20: Spearman correlation and significance between severity (outcome) and input variables

	correlation coefficient	significance (2-tailed)	significant at 0.01 level	significant at 0.05 level
SEX	-0.0367	0.0471		yes
AGEGRP	-0.0369	0.0457		yes
MECHAN	0.0001	0.9948		
NI1 (nature of injury)	0.2531	0.0000	yes	
BP1 (body part)	-0.0586	0.0015	yes	
CIRC_COL (circumstances of collapse)	0.0004	0.9830		
HELMET	0.0708	0.0001	yes	
ATV SEAT POSITION	-0.0875	0.0000	yes	
SEVERITY	1	n/a		

6 Conclusion

6.1 Work and Findings

The main objective of this thesis is to advise injury prevention programs on the factors that are central in predicting the severity of an ATV injury by creating a ANN severity prediction model for ATV injuries using the CHIRPP database. The minimum set of factors that can predict the severity of an injury were found to be: nature of injury, helmet, age group, mechanism, ATV seat position, circumstances of collapse, body part and sex. Statistical analysis supported the minimum set of factors chosen by the ANN.

The development of an ANN model involved finding optimal network parameters and was both time-consuming and labor-intensive. The process of finding optimal network parameters was automated using Matlab source code, which evaluates network parameters in a predefined range and accepts new network parameters that improve ANN performance but do not result in instability or over-fitting.

In addition, the previous stopping criteria for an ANN searching for maxima, which often stopped ANN training at unstable peaks. In this study, the ANN was modified to stop training once the network became stable and ceased to change for 500 epochs. This new stopping criteria made it possible to find a new set of optimal network parameters to improve ANN performance. The results are frequently a little lower than using the previous method developed by MIRG, but they are more stable and reproducible.

The ANN model was created with a classification rate higher than that of the constant predictor and with sensitivity and specificity rates comparable with those found in other ANN models. The optimal ANN architecture contained no hidden nodes or layers and gave a logarithmic sensitivity of 0.0896. The evaluation of the ANN model for the tests sets gave performance values with a logarithmic-sensitivity of 0.0914 ± 0.0126, a sensitivity of 44.44% ± 2.79%, a specificity of 83.93% ± 1.49%, a CCR of 69.67% ± 1.52% and an ROC area of 0.7191 ± 0.016.

The results showed that the optimal ANN architecture did not contain a hidden layer. Although this indicates that this is a linear model, the linearity may be due to the small database currently available or it could be due to the removal of variables that had a large amount of missing data. When data is randomly missing, the missing data can be imputed or variables can be removed without greatly altering the representation of the data. However, if the data is not randomly missing, it may indicate that certain data is missing for specific reasons. For example, missing ATV injury data may be due to variables that did not apply to a specific injury or because it was an urgent situation where only the most important data or only treatment data was recorded. Removal or replacement of missing data from urgent situations may result in a biased dataset [38]. Therefore, the removal of missing variables may have resulted in the removal of non-linearities, which would require hidden layers in the ANN. When more data is available, this investigation could be repeated to test if hidden layer architecture is applicable and if non-linearities exist.

Although ANNs are black boxes in that they do not explain the relationship between the inputs and output, the values of the weights and the reduced input set show which factors are important. In addition, a Spearman correlation can be used to find the quantitative relationship between the inputs and output.

6.2 Contributions

The summary of contributions made by this thesis is outlined.

1. Identified the factors that are central to predicting the severity of ATV injuries.

2. Showed with statistical analysis of factors, that an ANN model can be developed to explain the circumstances surrounding severe ATV injuries for use by injury prevention programs and parents.

3. Demonstrated that a feed-forward back-propagation ANN can be used to create a suitable injury severity model using ATV injury cases from the CHIRPP database based on performance measures.

4. This was the first study of ATV injuries using the CHIRPP database and the first use of ANNs to investigate specific injury variables within the CHIRPP database.

5. Showed that an ANN without any hidden layers is suitable for the ATV severity model because this architecture results in the highest value for the logarithmic-sensitivity performance indicator, which shows the ANN's ability to correctly classify severe and non-severe injury but focuses on the ANN's ability to classify severe injuries.

6. Created an automated approach using a new stopping criteria to find optimal network parameters, i.e. learn rate, learn rate increment, learn rate decrement, weight decay, weight decay increment, weight decay decrement, weight elimination scale parameter, momentum, and error ratio.

6.3 Future Work

This work is considered to be on going because there are so many possible applications of ANNs and an extensive amount of information in the CHIRPP database that can be analyzed. A list of possible future work to improve on this research is outlined below.

6.3.1 ANN

1. Modify the automated selection of optimal network parameters to locate the maximum performance during stable fluctuating periods of learning.

6.3.2 CHIRPP Database

1. To improve the database, the coding of each variable should be organized in a more logical order to suit the problem. For example, the rural variable is coded by the values 0, 1 and 3 corresponding to urban, rural and unspecified accident locations. A more sensible coding scheme should code the values 0, 1 and 2 into unknown, rural and urban. This coding scheme is more consistent because there is not a jump from code value 1 to 3 and it follows the order of increasing amounts of injuries.

2. Modify the CHIRPP accident reporting form to have multiple-choice questions for a reduced amount of misinterpretation of questions and easier translation of answers when converting data into numerical code for analysis, as well as, have the option to add other answers that are not available in the question and the option to add text descriptions.

3. Modify the CHIRPP accident reporting form so that there is a lower chance of erroneously filling out fields or leaving blank responses. This may be done by using the past responses collected by CHIRPP to give the user a larger array of responses to choose from and by having

the option for the user to give an alternative response. Blank responses may be prevented by adding a note indicating the importance of filling out each field and by asking that the person who collects the form to check for blank fields.

4. Increase the amount of severe injuries in the database by using re-sampling techniques. A larger amount of severe injuries may aid in training the ANN to detect severe injuries.

6.3.3 Statistical Models

1. Condense many fields into one single field (e.g. all lower extremity injuries together). Variables with a large number of fields may adversely affect ANN performance.

2. Utilize statistical methods of selecting key input variables to compare with the significant input variables found by the ANN.

3. Collaborate with Health Canada to investigate and model other types of injuries and outcomes found in the CHIRPP database.

6.3.4 Injury Prevention

1. To reduce severe ATV injuries, the major predictors of severity should be focused on with additional studies or investigations. The ANN effectively indicates major factors but does not reveal specific details about the exact role of each factor in ATV injuries. Referring back to the Canadian Paediatric Society's seven recommendations on reducing ATV injury, the results of this study do not conflict and many of their recommendations directly address the variables identified as severity predictors.

2. Create a specific pilot study to collect information specifically about ATV injuries and their root causes whether it be human error or a lack of adequate safety features. This information could then be used to advise ATV users and ATV manufacturers.

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Appendix A

Table A.1: Complete list of variables in the original CHIRPP database

Variable	Data Format
Hospital	Numerical
Postal code	Text
Gender code	Numerical
Gender description	Text
Ethnicity	Numerical
Ethnicity 2	Text
Age at injury	Numerical
Age group	Numerical
Age group 2	Text
Injury date	Numerical
ER (emergency room) visit date	Numerical
Year of injury	Numerical
Month	Numerical
Month description	text
Day of week	numerical
Day of week 2	text
Injury time	numerical
Injury time description	Text
injury event	text
Product involved	text
Place description	text
Location	numerical
Location name	text
Area code	numerical
Area code description	text
Context code	numerical
Context	text

Breakdown event	numerical
Breakdown 2	text
Mechanism	numerical
Mechanism 2	text
Intent code	numerical
Intent new	text
Industry code	numerical
Industry description	text
Occupation	numerical
Occupation 2	text
Vehicle seat position	numerical
Vehicle seat	text
Disposition	numerical
Disposition 2	text
Work injury	numerical
Work injury	text
Follow-up flag	numerical
Follow-up	text
sd1 (safety device) code	numerical
sd1 (safety device) description	text
sd2 (safety device) code	numerical
sd2 (safety device) description	text
sd3 (safety device) code	numerical
sd3 (safety device) description	text
bf1 (breakdown factor) code	numerical
bf1 (breakdown factor) description	text
bf2 (breakdown factor) code	numerical
bf2 (breakdown factor) description	text
mf1 (mechanism factor) code	numerical
mf1 (mechanism factor) description	Text
mf2 (mechanism factor) code	numerical

mf2 (mechanism factor) description	Text
cf1 (contributing factor) code	numerical
cf1 (contributing factor) description	Text
cf2 (contributing factor) code	numerical
cf2 (contributing factor) description	Text
noi1 (nature of injury) code	numerical
noi1 (nature of injury) description	Text
bp1 (body part) code	numerical
bp1 (body part) description	Text
bp2 (body part) code	numerical
bp2 (body part) description	Text
noi3 (nature of injury) code	numerical
noi3 (nature of injury) description	Text
bp3 (body part) code	numerical
bp3 (body part) description	Text
Event type	numerical
Event type 2	numerical
Sport	Text
Sport code	numerical
Sport code 2	numerical

Appendix B

Table B.1: Factor types

Factor Name	Factor Code
Home Furnishings and Accessories	101-152
Furniture	211-264
Kitchen Appliances and Equipment	311-392
Home Heating Equipment and Accessories, Air Cooling and Air Treatment Equipment	401-413
Cleaning Products, Devices, and Waste Equipment, Home Safety Devices	421-468
Outdoor Barbecues and Accessories, Outdoor Furniture	471-482
Swimming Pools and Accessories	491-496
Garden Equipment and Supplies	511-544
Baby Articles and Toys	551-593
Playground Equipment	601-610
Food	621-635
Clothing and Accessories, Skincare Products, Cosmetics and Accessories	641-675
Dental Appliances and Oral Hygiene	681-685
Hair Products and Accessories	691-702
Eye Wear and Accessories	711-712
Safety Gear, Protective, Health and Medical, Therapeutic Devices	721-744
Medication/Drugs, Alcohol, Street Drugs and Abused Products	750-786
Guns, Ammunition and Explosives	791-795
Audio or Audio Visual Equipment and Accessories	801-810
Optical Equipment, Arts and Crafts Supplies, Sewing Equipment and Fabrics, Smoking and Smoking Accessories, Paint	821-873

and Painting Equipment, Ladders	
Hardware/Tools and Accessories, Industrial Tools and Equipment	882-996
Structural Elements, Structures, Building Materials, Plumbing, Windows, and Doors	1001-1070
Sporting Equipment	1091-1097
Sports	1111-1145
Physical Activities and Associated Equipment	1151-1185
Chemical Products	1211-1293
Animals, Animal Equipment and Supplies, Insects and Spiders, Plants, Natural Environment, Environmental Elements, Water, and Public Use Items	1301-1399
Vehicles and Vehicle Parts	2011-3003
Products/Items Not Elsewhere Classified	3101-3119
Person	3121-3125
Unknown	3130

Appendix C

Table C.1: Missing values in the ATV database

Variable	Percentage of Missing Values	<20% Missing	<40% Missing
Sex	0 nb: 71.6% Male, 28.3% Female	✓	✓
Age	0	✓	✓
ET	36.5% nb: 63.9% English, 34.9% French	✓	✓
Day (of week)	0	✓	✓
CD (Creation Date of record)	0	✓	✓
MON	0	✓	✓
YR	0	✓	✓
Hour	16.8	✓	✓
Location	37.1	×	✓
Area	57.3	×	×
Context	2.4	✓	✓
Job Related	0 nb: 95.9% No, 4.1% Yes	✓	✓
Industry	96.8	×	×
Occupation	96.3	×	×
Breakdown	2.1	✓	✓
bf1 (breakdown factor)	65.5	×	×
bf2	84.9	×	×
Mechanism	0.1	✓	✓
mf1 (mechanism	0.1	✓	✓

factor)			
mf2	82.6	✗	✗
cf1 (contributing factor)	52	✗	✗
cf2	92.3	✗	✗
ATV Seat Position	26.3	✗	✓
sd1 (safety device)	56.8	✗	✗
sd2	This field was deleted due to the absence of data.	✗	✗
sd3	This field was deleted due to the absence of data.	✗	✗
Follow-up	0 46.8% Yes, 53.2% No	✓	✓
Group	0.1	✓	✓
ni1 (nature of injury)	0.9	✓	✓
bp1 (body part)	0.9	✓	✓
ni2	73.9	✗	✗
bp2	73.9	✗	✗
ni3	89.3	✗	✗
bp3	89.4	✗	✗
Intent	0 99.2 Unintentional	✓	✓
RX (Disposition, i.e. severity)	0	✓	✓
Local1-Local5 (Local hospital record keeping variable)	Unused	✗	✗
RURAL (Based on postal code, City, Rural, or unknown home address of victim)	0 75.2%=City=code 0, 22.6%=Rural=code 1, 2.1%=Unknown= code 3	✓	✓

Appendix D

Table D.1: Original ATV variables and definitions

Variable	Definition and/or Comments	Values
WH	what happened to the victim	text
Product	type of ATV and/or the name brand.	text
Sex	male or female indictor	1=male, 2=female
Date of Birth	complete date of birth	mm/dd/yyyy
Age	age in months	7-1031 months
Age Group	age grouped into subsets of years	1 < 1 2 = 1 3 = 2-4 4 = 5-9 5 = 10-14 6 = 15-19 7 >= 20
ET	ethnicity	11-119 British Isles, W./S./E. European, Semitic Languages, S. Asian, E./S. E. Asian
Day of Injury	the day the injury occurred	mm/dd/yyyy
Hour	hour of the day	1 – 24 24=midnight
Location	the location where the injury occurred	11-150 own/other home, residential institution, school, hospital, sport/recreation facility, street/highway, trade/service area, industrial/construction area, mine/farm, other,

		unspecified
Area	area of the location	11-99 room, structure, part of building/grounds, sports related, body of water, residual variables, unspecified
Context	context in which the injury occurred This field was removed as it refers to the aspect that the injury was ATV related.	11-99 transportation, occupational & educational, sports & physical recreation, leisure, household, maintenance, personal, other events
Job Related	injury on the job	1= yes, 0=no
Industry	The removal of Industry and Occupation was recommended due to the low percentages (<5%) of occupation related ATV injuries in CHIRPP [21].	10-189 agriculture/fishing/hunting,/forestry & mining, manufacturing, construction, transportation & storage, communication, retail, government service, education & health, accommodation/food services, other services
Occupation	see above	1101-8999 managers/administrators, professionals, trades, clerks, salespersons, plant & machine operators, labourers, construction
Breakdown	breakdown events This field was removed and replaced by circ_collapse and text information.	11-54 falls by the victim, loss of control of objects or movements, proximity to danger, acts by other persons/animals, other events
bf1	breakdown factor This refers to something that malfunctioned in the ATV, i.e. a faulty part in the ATV. This variable has 65.5% missing values.	factor type: 1=mechanism factor 2=breakdown factor 3=contributing factor factors: home furnishings, floor/window coverings, lights/lamps, linen/bedding, furniture, bathroom, kitchen appliances and equipment, laundry appliances and equipment, water heaters, home heating equipment, air cooling/treatment, cleaning products/devices, waster equipment, home safety devices, outdoor barbecues, swimming pools, garden equipment/supplies, baby articles, toys, playground equipment, food, clothing, skincare, dental appliances, hair products, eye wear,

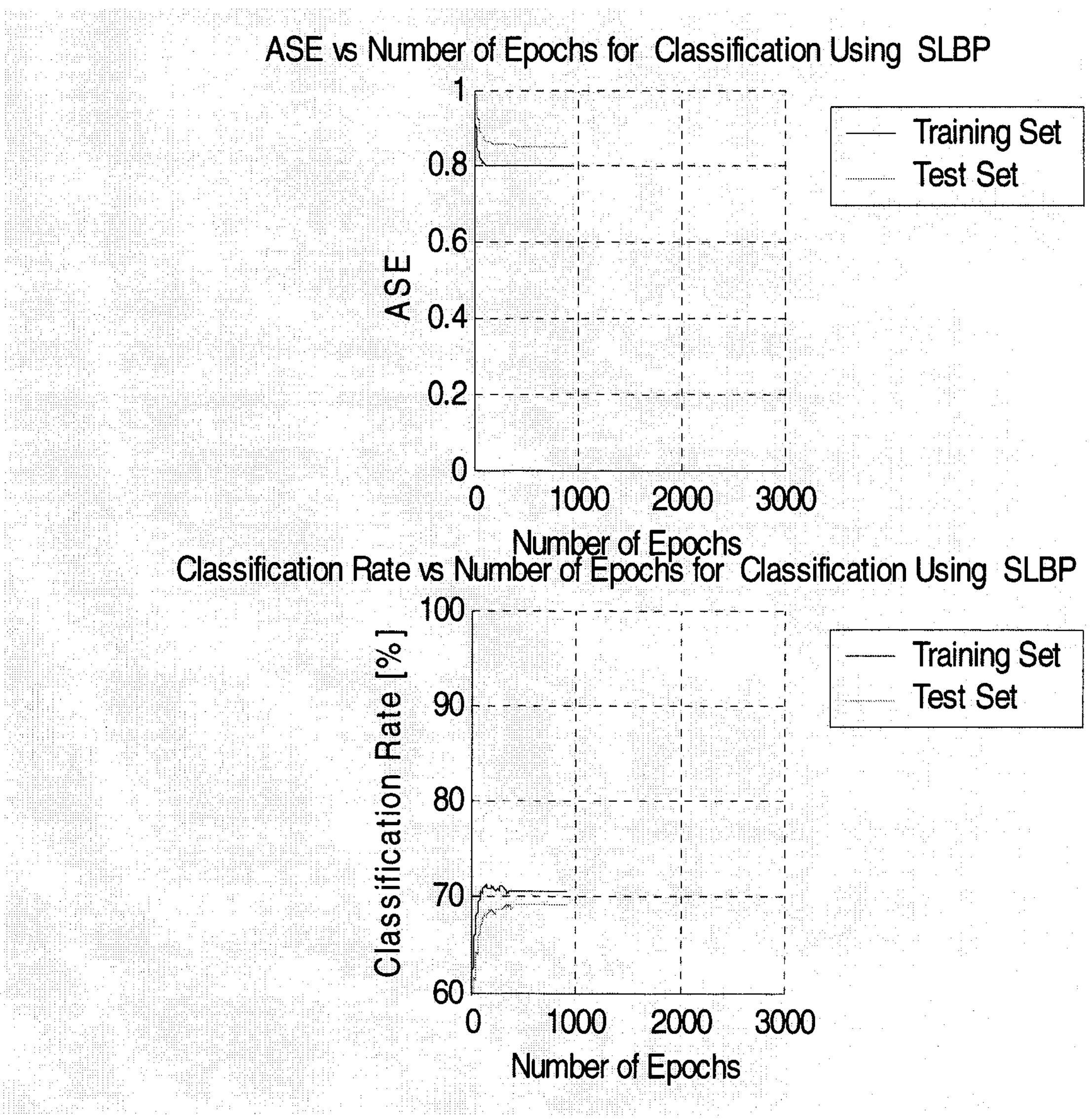
		safety gear, health/medical devices, therapeutic devices, medication/drugs, alcohol/abused products, guns/ammunition/explosives, audio visual equipment, optical equipment, arts/crafts/sewing supplies, smoking/accessories, paint/paint equipment, ladders, hardware/tools & accessories, farm equipment/produce, industrial tools, logging equipment, electrical/welding/soldering equipment, office/lab/school supplies, structures/structural elements, building materials, plumbing, windows, doors, sporting equipment, sports, physical activities/equipment, chemical products, animals/animal equipment, insects/spiders, plants, natural environment, environmental elements, water, public use items, vehicle/vehicle parts/accessories/products
bf2	breakdown factor two 84.9% missing values	
Mechanism	mechanism of injury	11-99 mechanical, chemical, thermal, electrical, radiation, asphyxiation, other
mf1	mechanism factor	see breakdown factor for factor list
mf2	mechanism factor two 82.6% missing values	
cf1	contributing factor Field is usually ATV in this subset, which is not as useful.	see breakdown factor for factor list
cf2	contributing factor two 92.3% missing values.	
Vehicle Seat Position	The "ATV Position" field replaced this field.	11-51 occupation of car/van/truck, passenger, occupant of motorcycle, snowmobile/atv/ppw, other
sf1	safety device The two values for this field are unknown/not wearing safety device and safety device use. The assumption was that an unknown field value is likely to indicate that no safety device was used. [21]	1-18 none, helmet, sports padding, protective boots/clothing, protective eyewear, seat belt, infant/child seat, inflated air bag, safety device, child resistant closure, other, not applicable, not specified

sd2	This field was deleted due to the absence of data.	
sd3	This field was deleted due to the absence of data.	
Follow-up	follow-up flag	1=follow-up refused 0=follow-up permitted
Group	injury group This field was removed as it refers to the aspect that the injury was ATV related.	10-22 falls, road traffic accident, motor vehicle/atv/snowmobile accident occupant victim, other, natural catastrophe, building/contents of building on fire, suicide/attempt, intended violence, encounter with animal/insect, abuse/sexual abuse, possible abuse
ni1	nature of injury, i.e. the type of injury	10-99
bp1	body part	110-999 head & neck, spine/spinal cord, trunk, shoulder & arm, hip & leg, multiple injuries, systemic injury, unspecified body part
ni2	73.9% missing values	
bp2	73.9% missing values	
ni3	89.3% missing values	
bp3	89.4% missing values	
Intent	intentional injury This variable was deleted since 99.2% of this data indicated the injury was unintentional.	10-19 accident, intentional self harm, sexual assault, maltreatment by parent/spouse/partner, unspecified assault, undetermined intent, victim of assault/possible assault, unknown intent, other intent
RX	disposition This is the outcome variable. It is treatment received, i.e. admitted, etc. This variable was reduced to two outputs: admitted and not admitted into hospital/fatal.	1=left the hospital without being seen 2=advice only 3=treated, follow-up if required 4=treated, follow-up required 5=short stay, observation in emergency 6=admitted to this hospital 7=transferred to another hospital 8=fatal 9, 10=intensive care unit.
Local	The "Local" fields are used by the individual hospitals and are left	

	blank in the database received from Health Canada.	
CD	This is the created date, which refers to the day that the record was entered into the system. This data is considered to be irrelevant for this study [21].	
DAY	This is the day of the week in which the injury occurred. This injury was deleted and replaced with a variable indicating whether the injury occurred on a weekend, which is calculated using the "Day" and "Hour" Variables.	Sunday=1 - Saturday=7
MON	month of injury Replaced with the season in which the injury occurred.	1-12
YR	Recommended that year was not important in prediction of injury severity [by Morag Mackay, Children's Hospital of Eastern Ontario]	1990-2004
RURAL	This variable was added based on postal codes. The postal code refers to the patient's home address. This could cause error because the location of the injury may not be the same as the patient's home location [21].	City=0 Rural=1 Unknown=3

Appendix E

Figure E.1: ASE AND CCR graphs for optimal network parameters



Appendix F

Hospitals involved in CHIRPP as of October 1997[4]:

- The Dr. Charles A. Janeway Child Health Centre: St. John's, Newfoundland
- The IWK - Grace Health Centre for Children, Women and Families: Halifax, Nova Scotia
- Hopital de l'Enfant-Jesus: Quebec City, Quebec.
- Centre hospitalier regional de Rimouski: Rimouski, Quebec.
- Hopital Ste-Justine: Montreal, Quebec
- The Montreal Children's Hospital: Montreal, Quebec
- Children's Hospital of Eastern Ontario: Ottawa, Ontario
- Hotel Dieu Hospital: Kingston, Ontario
- Kingston General Hospital: Kingston, Ontario
- The Hospital for Sick Children: Toronto, Ontario
- Children's Hospital of Western Ontario: London, Ontario
- Sioux Lookout Zone Hospital: Sioux Lookout, Ontario

- Various nursing stations: Fort Severn, Deer Lake, Wapekeka, Wunnumin, and Kingfisher Lake, Ontario

- Children's Hospital: Winnipeg, Manitoba

- Alberta Children's Hospital: Calgary, Alberta

- British Columbia's Children's Hospital: Vancouver, British Columbia

- Stanton Yellowknife Hospital: Yellowknife, Northwest Territories

- Various nursing stations: Inuvik, Keewatin, Gjoa Haven, Baffin, Fort Simpson and Fort Smith and Northwest Territories