

CRIME PREDICTION MODEL USING ARTIFICIAL NEURAL NETWORK

Project report submitted in partial fulfillment of the requirement for the
degree of

Bachelor of Technology

in

Computer Science & Engineering / Information Technology

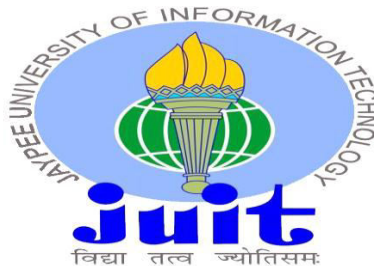
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Candidate's Declaration

We hereby declare that the work presented in this report entitled '**crime detection model using artificial neural network**' in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology in Computer Science & Engineering / Information Technology** submitted in the Department of Computer Science & Engineering and Information Technology, Jaypee University of Information Technology, Wagnaghat is an authentic record of my own work carried out over a period from August 2023 to May 2024 under the supervision of **Dr. Amol Vasudeva** (Associate Professor, Department of Computer Science & Engineering and Information Technology).

The matter embodied in the report has not been submitted for the award of any other degree or diploma.

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CERTIFICATE

This is to certify that the work which is being presented in the project report titled '**crime detection model using artificial neural network**' in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology in Computer Science And Engineering** and submitted to the Department of Computer Science And Engineering, Jaypee University of Information Technology, Waknaghat is an authentic record of work carried out by Shivanshu Mehta , 201203 and Yashaswi , 201260 during the period from January 2024 to May 2024 under the supervision of **Dr. Amol Vasudeva** (Associate Professor, Department of Computer Science & Engineering and Information Technology).

I also authenticate that I have carried out the above-mentioned project work under the proficiency stream Information Security.

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The above statement made is correct to the best of my knowledge.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
CNN	Convolution Neural Network
GIS	Geographic Information System
KDE	Kernel Density Estimation
KNN	K-Nearest Neighbour
LDA	Linear Discriminant Analysis
RNN	Recurrent Neural Network
RTM	Risk Terrain Modelling
VPD	Vancouver Police Department

ABSTRACT

One of the biggest and most prevalent issues in our society, crime prevention is a necessary endeavor. Numerous crimes are committed daily in large numbers. This calls for recording all crimes and compiling them into a database that may be accessed later. The current problem faced are maintaining of proper dataset of crime and analyzing this data to help in predicting and solving crimes in future. The objective of this project is to analyze dataset which consist of numerous crimes and predicting the type of crime which may happen in future depending upon various conditions. In this project, we will be using the technique of machine learning and data science for crime prediction of city of Vancouver, Canada crime data set. The city of Vancouver's official open data portal is where the crime statistics were taken from. Later the dataset is analyzed and pre-processed. All of the results arrived during the analyses of the dataset are shared in this report. Also the results arrived the pre-processing of dataset are also shared in this report. Next in order to predict a model neural networks will be used and using these a model will be made which will predict crime with high accuracy. To train the model we analyzed and

pre-processed the data which is already shared in this report. After this we go to the next step which is training and implementation of networks. Here we discuss the 4 network we have trained highlighting their input ,output, epoch cycles ,losses ,accuracy and timeline of crime.

CHAPTER 1: INTRODUCTION

The cases and forms of crime are perpetually changing while no specific reasons or underlying causes are reasonably forecasted. What we have is a constantly changing environment due to unspecified fluid reasons. Analyzing and detecting crimes with effective tools at hand is often a measure directed to find the ones who have done the wrong thing. The identification of suspects in an early stage makes it possible to purposefully be placed, their strength is focused on the most in-seizing cases and play a role of the prediction work. On the other hand, plan burglary and arson have declined as stated by the Bangladesh Office of Crime Record, but opposite to this, the cases of child abuse, rape, polygamy and other more dangerous incidents have increased by many folds. The approach which in fact could show the result becomes more error-free with every successive try, but at the same time cannot guarantee that the result might be applicable all the times.

It will show either different that the society and the whole community decided, or the singularity in the crime's character that has many features. To reiterate, the studies conducted earlier has shown are some of the variables which are directly connected to crime prediction they include poverty, education, employment and climate. In conjunction to Vancouver, the largest metropolitan city of Canada and the most populated one, we have to account not only for the general culture and ethnic diversity in the community. However, while more holistic, integrated and collaborative approach involving the participation of all the community sectors in crime prevention has been creating great hope regarding the rise of the crime rate, Vancouver has seen one of the most significant drops in the number of reported crimes. Not achieving the termination of the issue in 2017 is something we need to stop messing around with. However, the issue of car break-ins and thefts is also unresolved. It still exists.

In the starting of 2016 December, the VPD (Vancouver Police Department) released prototype as prediction crime system like forecasting crime such as home going-ins. In the Vancouver

metropolis, the break-in rate of houses sold in the last month registered 25.4% decrease. The forecasting model which is establishing the picture of crimes which are difficult to be ignored is embodied in the term “crime diagnostics”.

In fact, the situation is not different in the cities worldwide where police departments remain an authority to pay a lot sum of money just to select the crime patterns, come out with the actual thieves' plans and develop proactive techniques of the crime solving. This was just that based on the evaluated criminal statistics and a comparison to the data from the recent years provided information about the common crimetrends of the junctures of years, months or even days. On the other hand they always had a possibility of intercepting numerous undercover officers and got a great advantage of the observation over the whole city. As such anticipatory few of them could be in guard to the abnormalities going on as well as alert the rest. Unfortunately, such strategies sometimes were just too costly for the crime situation, what is the most important here, they were way too general and a whole bunch of relevant factors were left unaccounted for. Instability and unpredictability of crime, which in its turn is influenced, by variety of factors among them social elements, terrain, weather, and economics are ones that are not in the framework of the historical data leaving the model to have a low accuracy. Thanks to the development of deep-learning neural network algorithms and high-performance computers, it is a widely accepted common opinion that crime prediction can be considered as one of the emerging areas along with many others.

It comes as a means for the display of definite patterns of the links between the crime and other basic factors. Nevertheless, the deep learning technique of crime prediction is an area which has yet to be fully researched and requires more work and development than other areas such as computer vision and generative modeling, etc. Deep learning networks are developed specifically to reduce huge feature engineering, and to learn from large datasets. The symbiosis of criminality, its multifactorial nature, time and place, the manner and its essence are the reason why it is a very validate neural network forecast.

Problems in the existing system

Different researchers have chosen to tackle the issue of crime prediction and the subsequent development of separate remedies for reducing crime rate to have been the diversified research that has been done by different scholars. The ability of the model to make an accurate forecast for

business growth depends on them choosing the appropriate attributes as well as being created on certain data.

The cold prediction spots in London, UK were characterized using the human behavior data that was collected from mobile phone network signaling information together with demographic data sourced from actual crime data. Weka, an open-sourced data mining program, and 10-fold cross-validation were chosen over Decision Tree and Naive Bayesian, two classification methods, to test the predictive accuracies of them.

The 1990 US Census, the 1990 US UCR, and the 1995 FBI UCR were united to provide the parameters of socioeconomics, of crime, and of law-enforcement, which are the basis of this study. The Studied Factors which Change from time to time Were the Driver, Weather, Vehicles, Road Conditions and the many more. These were the emphasized aspects of the Examination. The accident dataset, containing a total of 18288 observations data, was used to predict the consequences of a particular accident using KNN, Naive Bayesian, Decision Tree as supervised classifiers. In spite of the fact that the three models' differences between the predicted and actual values vary from 79% to 81 %, a good model is one that accurately predicts as opposed to overestimating.

The proper and competent investigation of the volumes of crime files is the major impediment to crime prediction. Data mining is an easy tool to rapidly and accurately explore latent patterns in massive criminal data a set. the better precision along with less mistakes of the criminal data mines assist in the predictability of crime being more and more accurate. The Hayward Police Department relied upon the University of Arizona Coplink project to build in place a general data-analysis framework.

Majority of studies on predicting crimes is aimed at security of what is commonly referred to as hot spots or rather places with high crime levels. The 's conducted a research which is it or not the RTM method (Reduced Territorial Modeling) or the KDE method (Kernel Density Estimation) worked more precisely. These sensors were limited to a particular area, and forecasts were linked with regions rather than pinpointing specific locations. The model technique such as the historical and spatial-temporal histogram-based that was employed for the statistical methodology used to predict the crime hotspots ,(LDA) and KNN, thereby improving accuracy. The purpose of comprehension of crime detection could be accomplished through deployment of

crime scene scanning techniques like the ones that augment the neural network performance shown as AI. such as Gamma test method is one of the best techniques to identify the crime hotspots in Bangladesh. we used a machine-learning system that was modeled by spatial analysis. It incorporated visualization and RPPT to map drug crimes in Taiwan. Hotspots and future growth areas were discovered.

Methodology

A working model which can be used by predictive modeling is developed in this way. The learning machine algorithm used in the method learns in particular features from the training set for creating such predictions by the dataset.

Two subclasses of predictive modeling are regressive and pattern polarity. To foresee the levels of continuous variables, the models using the regression are built by means of detection of dependencies between variables and trends among them. But the pattern classification would rather be of distinction with the class or categories of data as the output. The sample pattern problem of weather forecasting could be expectancy of light, heavy, or balmy weather. Classification is also an implementation of model that follows this rule. As pattern classification tasks come in two parts—Supervised learning and unsupervised learning—they can be broken down into these two groups. In supervised learning, both the class labels in the training set as well as the model that is constructed with them are obvious. In a supervised learning situation, there will be a known training dataset with a particular output, whose purpose in training will be used for prediction of unseen data

Introduction to the project

Crime prediction is the key hurdle to minimize crime rate of society with the idea of law enforcement agencies placing the most effective patrol schemes Many social benefits will come out of an improved security situation because of lesser criminal incidents. On the one hand, public safety and economic violence will also run concurrent, thus increasing. Nevertheless, forecasting the performance of criminals' activities represents a complex story. In space-time distributions, crime incident occurrence is uneven and it is case-specific. Among the main criminal activities in Vancouver are as follows: theft, drug offences, and assault. We notice the

differences in how their spatial extent is distributed. The likelihood

it is not certain whether a criminal action will take place at a certain time and a place or not because it has to do with numerous perturbations. Population and provided healthcare/transport/crime accepting facilities/human transferring and so on.

This study intends to pick out the specific R zones of a given city and compares the areas of particular times of the year to observe the types of crimes affecting them. Other not-so-sometimes violent and extreme crimes like theft, criminal trespass, drug offence, offence involving traffic, fraud, and assault are also debated at length. An unlawful entry into someone's property with the intent of permanently or even reducing robbery of valuables from that property, whether the person's intention is to steal the property or misappropriate it, is commonly known as burglary. If it can be proved that a criminal might have the intention of entering an office, bank or store to commit a crime and this deprivation by force has been done illegally it should be classed as a crime. Not only the dealing, production, harvesting and trafficking of any drug but also any other substance taken at natural level or synthetically by humans falls under the umbrella of existing law as an appropriate offence. This includes keeping tabs on not just traffic congestion, but also activities carried out on roads like driving licence or car/bike registration, status of vehicle allowed or not permitted for use, all through to road walkers. The Queensland police themselves on fraud saying that the best way to describe fraud is, the act of people or an organization which is meant to fool others who they are behaving. Law is considered as any violence, the term encompassing physical injury as well as mental harm to another individual. The word 'physical abuse' cover all the actions related both to touching the body without permission or all bodily actions as hugging, kissing and any kind touching outside their body. This research focuses on two issues: firstly, via applying the latest available technology, we are proceeding with a project concerning the short-term forecast of crime events. Besides that, a day is made up of 8 long equal intervals (each 3-hr interval) and the task is to tell in which of the intervals a crime would be committed. It's possible to predict crimes in finer temporal outcome and the police can use it to create a dynamic patrol strategy. The officers will increase probability to be more successful in reducing crime rate.

CHAPTER 2: LITERATURE SURVEY

Machine Learning

Introduction

Machine learning algorithms are one of the most critical part of intelligence areas such as learning, prediction and inference by systems or software programmes not only that but also getting them more accurate without explicit instructions. Basically, an information processing procedure uses the data as the input and trains the system or model by using statistical inputs so that it is logically clear to identify or predict the correct outputs. The outputs may be further improved with newer data available.

<https://writeelite.com/blog/write-about-some-past-memory-essay>Next, the technique needs to identify the resulting patterns or resemblances within the dataset. After that, it needs to optimize or adjust the system if necessary [6].

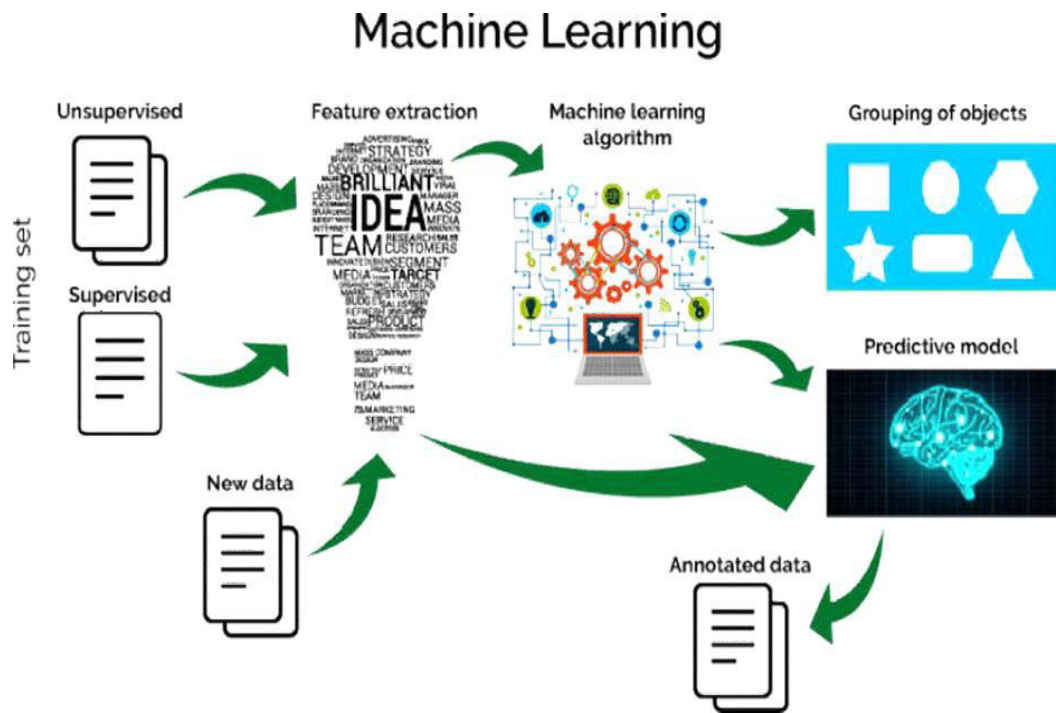


Figure 2.1: Machine Learning[1]

Working of Machine Learning.

The first step of machine learning which is having input dataset, will be made up by images, articles, tables and other types of data. Another aspect is that multiple pre-engineered machine

learning approaches are being utilized on the input data for the purpose to forecast the output and generate “these, in turn, are satisfactory”. Be it clustering algorithm that puts the data into groups or logic finding algorithm that looks for patterns in the dataset. along with supervised and unsupervised methods, two main groupings for machine learning algorithms are existed.

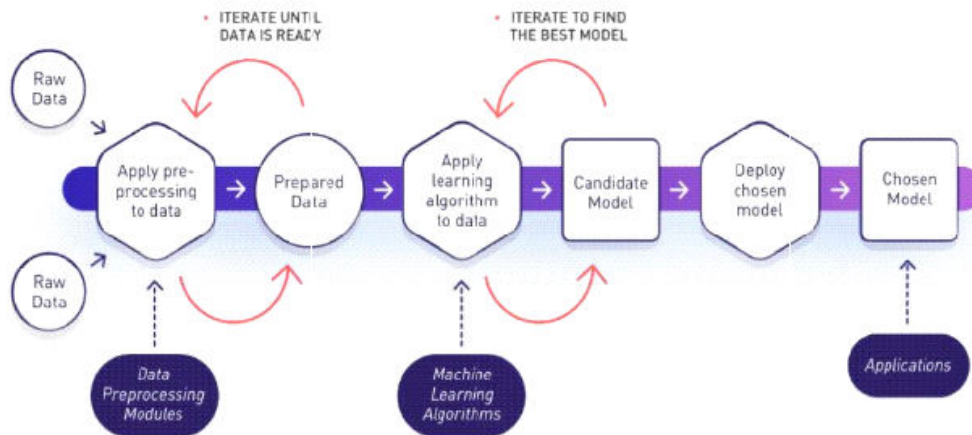


Figure 2.2: Workflow of Machine Learning Algorithm[1]

2.1.3 Types of Machine Learning

Supervised Machine Learning

These algorithms are very efficient for datasets that have not used enough data and that does not have previous outputs and outcomes to predict the next outcomes based on the learned information. In this case, the software runs the known dataset and it then yields an inconformed function, this can become the new model for predicting new dataset output. In addition to the detection of the faults, the analysis of the data and ultimate comparison of the seven-result outcome with the previously stored data is also carried out, to identify the errors and train the model more effectively.

Unsupervised Machine Learning

This Neural Network differs from supervised machine learning algorithms, in that the latter ones

are teaching the model to classify or label the datasets, that have not been trained before. Yet, by way of putting outliers aside, unsupervised learning enables the system to understand a hidden structure or phenomenon in the unsupervised information and then conduct the predictions by the use of such patterns.

Semi-supervised Machine Learning

The advantages of both supervised and unsupervised algorithms are semi- supervised algorithms in that they produce enhanced and powerful classifiers. These kinds of algorithms include a model that trains over labeled and possibly unlabelled data and sometimes require only a little bit of labeled data and a lot of unlabeled data that are used in parallel. This is often used with data that requires both expert and respective sources of training and learning because it assists the model in establishing correct answers and making predictive assessments.

Reinforcement Learning

Through implementation of the motions and observing consequences of the actions, an agent learns how to behave in a certain environment by applying reinforcement learning methods. It is a directions-based technique which features machine learning. If the AI bot performs the good activities, it gets compliments and if the last ones then is punished or given a negative feedback. This method is opposite to supervised learning because it self-teaches itself to use reinforcement feedback in the absence of labeled data . The system can only obtain knowledge from experience itself since there is no labeled sample.

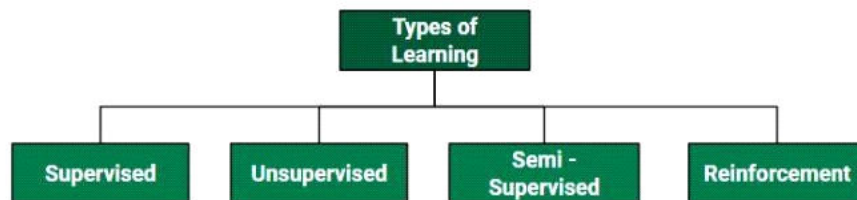


Figure 2.3: Types of Machine Learning [3]

NEURAL NETWORK

Artificial Neural Network

The Neural Networks or the ANNs mechanics are a model of information processing that is

inspired from the complex way a living nervous system, such as a brain, processes data. It consists of numerous processing units, that are intimately "linked" so that they join in the process of solving a certain problem.

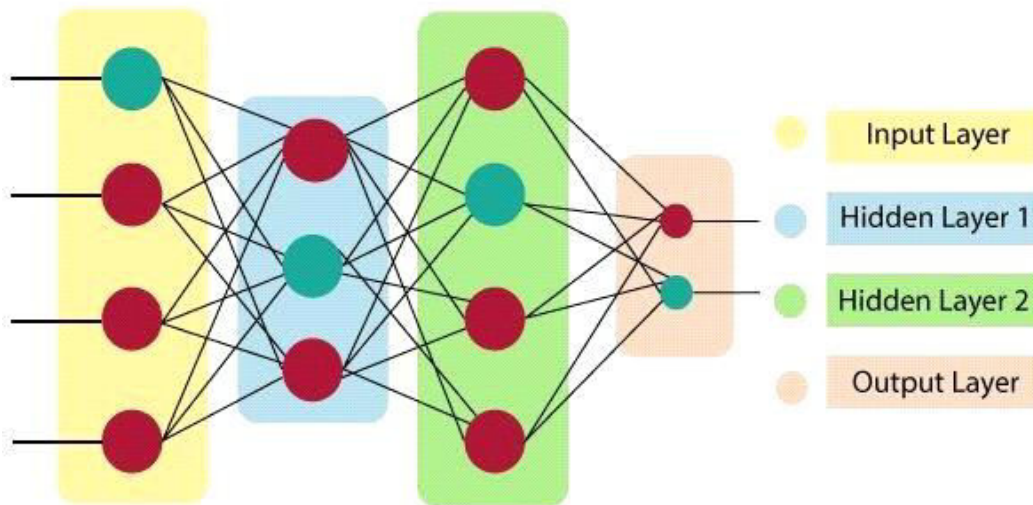


Figure 2.4: Artificial Neural Network[4]

Convolution Neural Network

A ConvNet/CNN (Convolution Neural Network) is an autonomous technique, which not only is able to give to various elements / articles of the picture importance (the learnable weights and biases), but also to distinguish them. Unlike other classification techniques, a ConvNet definitely requires less thorough preprocessing when compared to the other. ConvNets can understand these filters and features by themselves, against basic strategies in which filters are calculated manually and often without adequate training data.

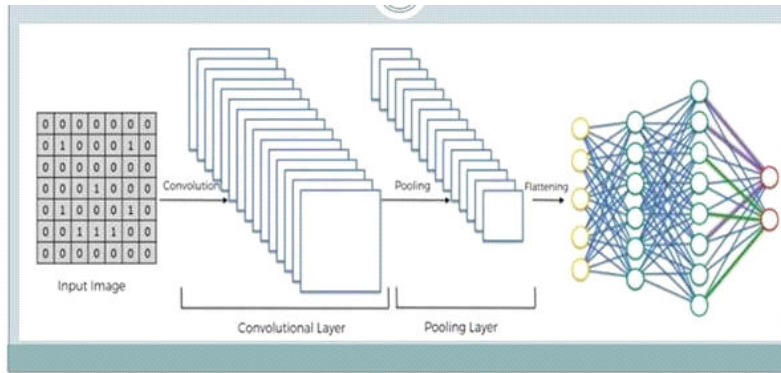


Figure 2.5:Convolution Neural Network[4]

Recurrent Neural Networks

The recurrent neural networks are capable to follow the illustrious past and can accordingly use that previous knowledge in the course of their decision-making process. RNNs are able to recall the information gained from prior inputs in their subsequent output, regardless of how the RNNs learn themselves during the training phase thus. Being the network's part, it's a must. RNNs have a constituent state vector (hidden) that presides over the context based on earlier inputs/outputs. RNNs may receive one or more input and may at any time output one or more target vectors, but the target output will be contextually dependent on both, the earlier inputs and the input weights will be given to this contextually dependent output as well. This means that successive inputs can have a conscious effect on the previous term throughout the series.

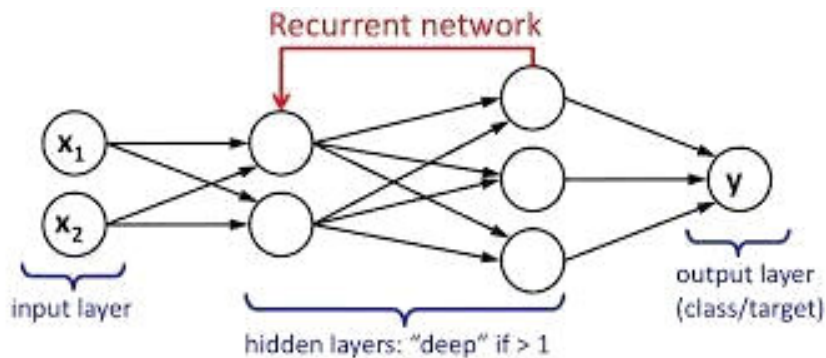


Figure 2.6:Recurrent Neural Network[5]

ACTIVATION FUNCTION

They basically perform the task of transformation of a given input signal into an output signal which can be used as a node in an ANN network. Dealing with the whole of the passed on data as input forms the next layer of the stack. By doing the multiplication of each element with its corresponding weight and bias, the activation function produces or leads to a total neural activation, which in turn stimulates the transduction of a potential action. This objective of bringing about a change in the activation function which is being expressed out through the neuron is one wherein non-linearity is achieved.

Sigmoid Activation Function (Logistic function)

S-shaped curve having the range between 0 and 1, is the mathematical function that is referred to as sigmoid function. As a result, it will be used in models in which the output should be expressed as a probability value as well, than just some number value. This function may reduce the neural network becoming stuck in the training process when they are given large negative input values.

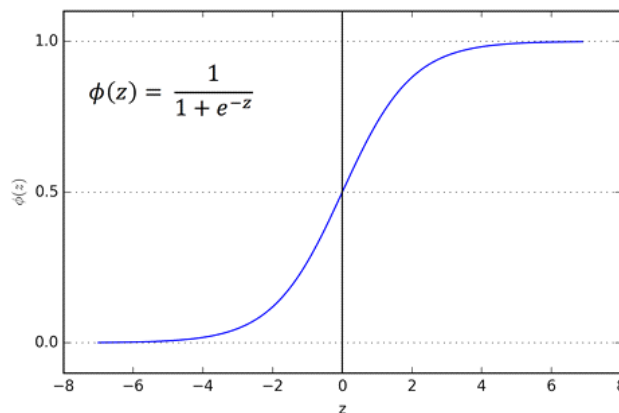


Figure 2.7: Logistic Function[9]

Hyperbolic Tangent Function (tanh)

The Hyperbolic Tan Function which is similar to the Sigmoid often leads to better performance by its nonlinear nature. The more layers we have, the better. The function encompasses (-1,1). The

primary advantage of this function's design script is that only inputs that are near zero get mapped to outputs that are close to zero while strong negative inputs result in a negative output. Hence, training can't freeze up due to the role of feedback loops.

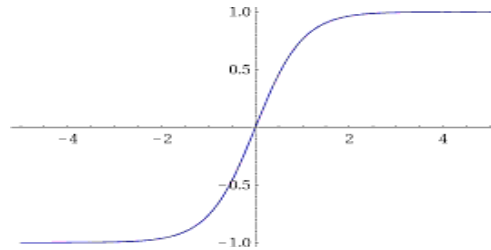


Figure 2.8: Hyperbolic Tangent Function[12]

RmsProp optimizer:

A RMSProp/root-mean-square-propagation (RMSP) algorithm specially designed for the optimization of AI neuronal network usage is a method for training neural networks. The RMSprop optimizer will limit the vertical wobbles at a height of RMS. Convergence time can be enhanced and the direction vector is flattened by increasing the step size and selecting bigger horizontal stride.

LOSS FUNCTION

In an artificial neural network in an artificial neural network throughout a predictive probability that is provided by a label or a set of labels there is a function called cost function that is used for identifying the level of performance in an artificial neural network. Mean squared error is easily the most basic and common cost function used in the neural network from a pool of diverse and often complex candidates. Fitting the weights and parameters of the neural natural network to give the best minimized cost/loss function is our last assignment in training the neural natural network. Therefore, our approach was based on a well-known optimization algorithm, which is called Gradient Descent.

Binary Cross entropy

When deciding whether to do yes or no things, e. g. labeling items using several tags, one has

binary cross entropy as a loss function. The generation of this kind of error is an appealing quality visual teaches us how accurate our model is in predicting. For that, the model would attempt to classify examples into each the class that may be active in a multi-labels scenario where an example may have a multitude of labels concurrently at a time.

$$L(y, \hat{y}) = - \frac{1}{N} \sum_{i=0}^N (y * \log(\hat{y}_i) + (1 - y) * \log(1 - \hat{y}_i))$$

Figure 2.9: Equation

CHAPTER 3: SYSTEM DEVELOPMENT TOOLS

In the processing of algorithms, the universal system which is in the project entails algorithms that are proposed.

Windows 10 (64-bit)

ANACONDA

Python

4 GB RAM

Intel(R) Core(TM) i3 3120M is a low-power, yet satisfying performance CPU with two processing cores. 50 GHz

WHY PHYTON

Python is an over-the-worldly programming language that is easily interpretable and takes the least time to read. Furthermore, Python offers a package of various tools as add-ins that can accomplish the most complicated problems, allowing solo project development. The Python supports all sorts of file libraries, which include complex ones for working with texts, images, and audio files. Highly adaptive Python can neatly manage to run alongside another operating system. Since help and even a help in the programming will always be useful, in the programming community of Python, it is possible to get help any time.

WHY ANACONDA?

Thus anaconda is well-known to be the outstanding environment because it has all libraries

pre-installed, the user won't have to do them manually other than that. It provides people with the ability to analyze data, do machine learning, and pull the forecasts through the more than 100 packages.

WHY SCKITLEARN?

Customarily machine learning specific Scikit Learn is a python library which displays a list of all regression, classification, and clustering algorithms.

WHY PANDAS?

Panda is a popular Python library that boasts of by being high-performance and used in open source. This software brings for data classification and analysis techniques, and it is easy to work with. The library is great in the field of research, business and industry science.

WHY MATPLOTLIB/SEABORN?

Seaborn is a plotting package that is capable of creating beautiful graphs in Python. From Seaborn a high-level interface is provided for great graphics' construction with the aim of providing a user-friendly statistics environment[21]. Simplex plotting is a task typical for MatplotlibBar charts, pies, lines, scatter plots, and such other indexes are as a rule used in Matplotlib visualisation.

Why KERAS?

Python-based Keras is a free software that is specialized in critical neural networks. It also comes with a number of options to build upon it such as TensorFlow, Microsoft Cognitive Toolkit, R, Theano and PlaidML. Main concern lies on users' experience, simplicity, and scalability that let the deep neural networks experiment easily.

CHAPTER 4: DATASET ANALYSIS

DATASET USED

By implementing an easy acquisition of data for the project, we sourced all information from city of Vancouver's set of public data. The tables directly below are all the datasets we employed in the project; they are discussed intensely in later sections for addressing specific cases.

Crime Data

The datasets that are raw came from the open data portal of Vancouver. Our dataset for this study will contain two components, namely crime and neighbourhood. Three years ago, the VPD started to compile the crime data, and now it updates that information on Sunday mornings at the latest. In it, one will learn how the nature of the crime is narrated, and what specific settings and occasions the offence happened. The spatial objects representing the 22 regions of the city's Geographic Information System are defined in dataset of neighborhoods (GIS). For mapping in this project the neighborhood dataset is being used while for data analysis the crime dataset is being used. Statistics of the crime [17] set was a first dataset we got from the website. The dataset's columns included the following information: The dataset's columns included the following information:

Type of crime

Year

Day

Month

Hour

Minute

Block of crime

Neighborhood of crime

UTM Zone 10 este elementul primordial al crimei.

The Y coordinate that represents crime in UTM Zone 10.

Latitude

Longitude

	TYPE	YEAR	MONTH	DAY	HOUR	MINUTE	HUNDRED_BLOCK	NEIGHBOURHOOD	X	Y	Latitude	Longitude
0	Other Theft	2003	5	12	16.0	15.0	9XX TERMINAL AVE	Strathcona	493906.5	5457452.47	49.269802	-123.083763
1	Other Theft	2003	5	7	15.0	20.0	9XX TERMINAL AVE	Strathcona	493906.5	5457452.47	49.269802	-123.083763
2	Other Theft	2003	4	23	16.0	40.0	9XX TERMINAL AVE	Strathcona	493906.5	5457452.47	49.269802	-123.083763
3	Other Theft	2003	4	20	11.0	15.0	9XX TERMINAL AVE	Strathcona	493906.5	5457452.47	49.269802	-123.083763
4	Other Theft	2003	4	12	17.0	45.0	9XX TERMINAL AVE	Strathcona	493906.5	5457452.47	49.269802	-123.083763

Figure 4.1: First five rows of data

The overall dataset was split up into 480724 crime facts alone spanning the duration from 2003 to 2017. Thus, though for some of the them it was locational and time data that was cloaked for the private reasons. These being all useless for the purpose, eliminated them from the lot only to be left with a mere total of 476290 cases to crease.

Neighbourhood Data

To next, we selected a data set from the open data catalogue Vancouver, which is a list of neighborhoods in this city[18]. We include here 2 columns to this dataset: The 'Latitude' and the 'Longitude', where we add the specific center latitude and longitude for each particular neighborhood. This second dataset consisted of the following columns:This second dataset consisted of the following columns:

Map ID

Neighbourhood Name

Neighbourhood Center Latitude

Neighbourhood Center Longitude

	MAPID	NAME	Latitude	Longitude
0	SUN	Sunset	49.218650	-123.091376
1	MP	Mount Pleasant	49.263060	-123.099888
2	RP	Riley Park	49.244679	-123.103239
3	CBD	Downtown	49.279255	-123.119137
4	KITS	Kitsilano	49.265663	-123.166947

Figure 4.2: First five rows of neighbourhood data

ANALYSIS

From the Figure 4. 3 but we can show the statistics may a bit different over the last 15 years, steal-from-the- car happened the most which are the most common. In 2017 this number rose to over 5,00,000 cases. Moreover, the fact that there is no mention of homicide and fatal vehicle collision or of pedestrians being hit by cars is a good indication of the positive consequence of the airline’s low emissions numbers for the last 15 years.

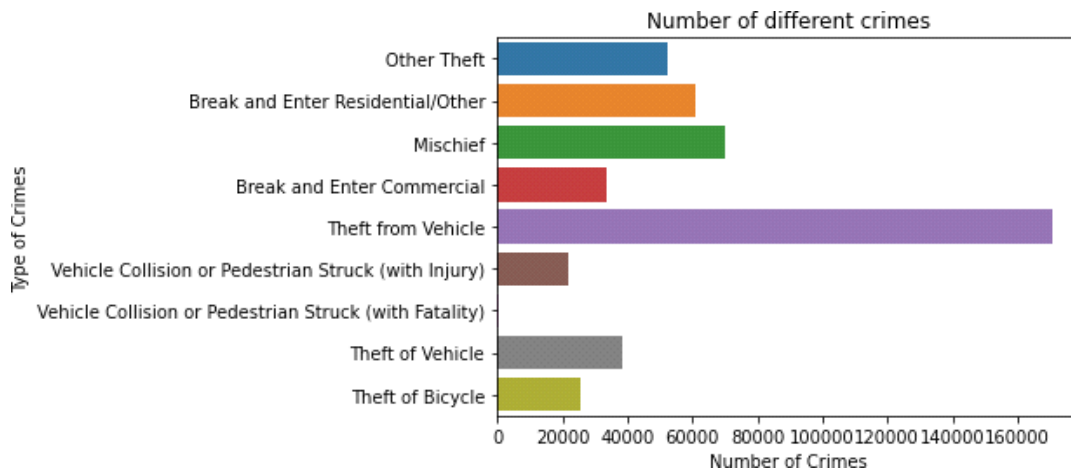


Figure 4.3: No of different crimes

From the Figure 4. 4, 2004 had the cases number recorded with the biggest number compared to all the other years. Beside 2006 one can observe that consecutive number of crimes gradually downward and reach to 2011 levels. Now between 2013 and 2017 it once again starts the climb,

but the steepness is less dramatic. In 2017 there was a very sharp drop in cases investigated by the police in the number of cases around 20,000.

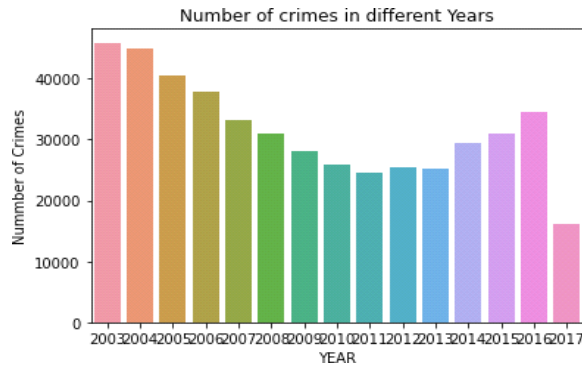
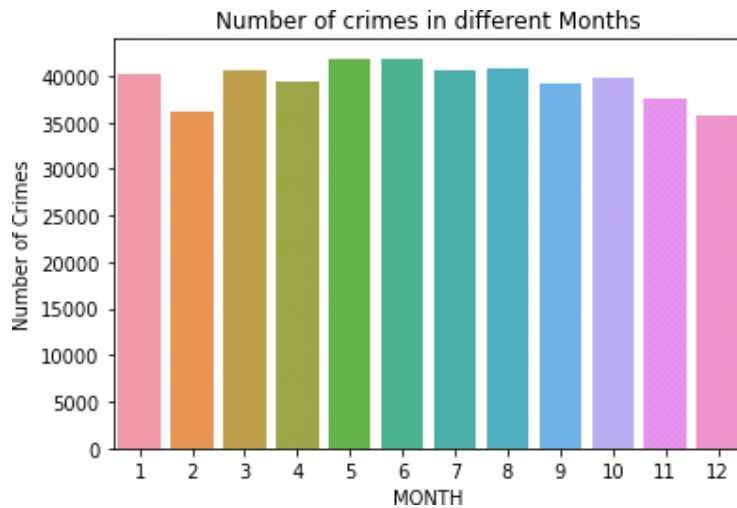


Figure 4.4: Number of Crime per Years.



In the Figure 4.5, Overall, the monthly number of cases due to this disease reported in 15 years is displayed. The figure above shows that for every month, we had nearly equal number of cases reported. This average number of reported cases stood at approximately 40000.

Figure 4.6, reports crime incidents on every date during 15 years with total of case reports per month shown as graph. The last day of each month, the month being 31 days, the number of test positive cases reported was least around 10,000. We came to a resting point nearly 16000 times all in all every day.

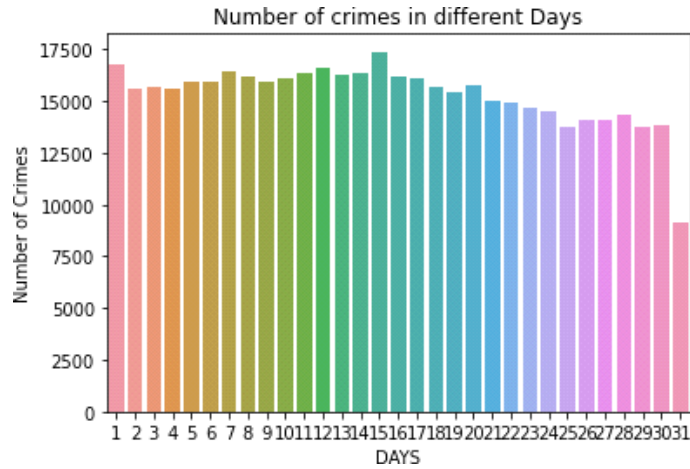


Figure 4.6: Number of crime per Day

Fig. 4 (Bar Graph) display suicide among women below the age 34 between 2013 and 2017 is shown below. 7 demonstrates that more crimes occur in the night-time and the mid-night peak frauds appears at 9. 00 pm. Clinical data did confirm that the sunny-side up trend continues, as shown in Figure 4. Though it is already acknowledged as the stage when you can came out of the closet, it is still perceived by others to be the most deadly and the safest we can ever have in our lives.

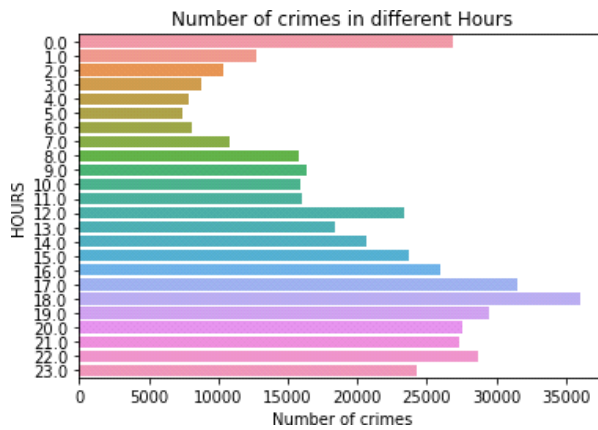


Figure 4.7: Number of crimes per hour

Figure 4.8 concerns the statistics of crime reported on the areas and parts of Vancouver. Therefore, if we go through the graph, central Business District will be known as the most active area in comparison with all. On the peak of cases count, in Downtown 90000 is the maximum. No city can surpass West End. It is the second most dangerous city of the country. When it was compared to other cities, some of which reached more than 10000 cases, it can be referred to as

the safest neighborhoods in Vancouver.

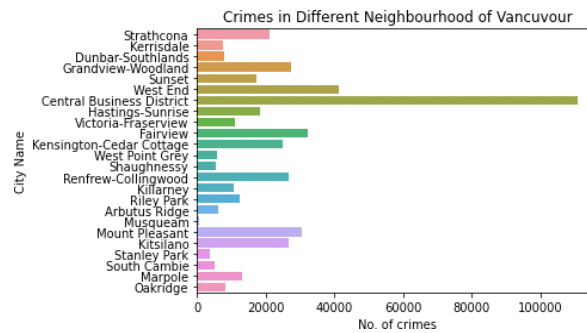


Figure 4.8: Number of crimes in neighborhood of Vancouver

Figure 4.9 consist of a list which also shows the number of crimes in neighborhood of Vancouver.

Central Business District	110947
West End	41352
Fairview	32161
Mount Pleasant	30536
Grandview-Woodland	27180
Renfrew-Collingwood	26761
Kitsilano	26699
Kensington-Cedar Cottage	24941
Strathcona	20919
Hastings-Sunrise	18126
Sunset	17396
Marpole	13083
Riley Park	12521
Victoria-Fraserview	10819
Killarney	10475
Oakridge	8037
Dunbar-Southlands	7746
Kerrisdale	7447
Arbutus Ridge	6066
West Point Grey	5871
Shaughnessy	5426
South Cambie	5212
Stanley Park	3775
Musqueam	532

Name: NEIGHBOURHOOD, dtype: int64

Figure 4.9: Crimes per neighborhood

CHAPTER 5: DATA PRE-PROCESSING

Data pre-processing is an approach which helps us to transform the raw data to process or to consolidate the unprocessed data to make it usable. Here, we have a distinct dataset containing the type of crimes in Vancouver area; therefore, this dataset will be used for the purpose of predicting the crimes and help the police to migrate their strategies concerning the crime rate and the techniques which are being used to reduce the rate of the crimes in this area.

The garbage values that are in the dataset we are using to abuse crime can very bad for us, making our data garbage also because we will be training our machine in the bad way and we will give you wrong results for the involvement and also become harmful. In our situation, we will want our model to determine the location of crime which is why we need accurate data so that we have a high level of speed while predicting crime.

Data pre-processing consists of following steps:Data pre-processing consists of following steps:

Data quality assessment

Data cleaning

Data transformation

Data reduction

DATA QUALITY ASSESSMENT:

A data quality assessment is a basic and first step for data pre-processing; it includes quality evaluation. That's the point. We shall take a close look at our dataset, and also pay attention to the quality of the dataset. Furthermore the dataset should be related to our project for us to be in a position to make use of it and also keeping the consistency of the dataset should be done. Data quality assessment includes such errors as scrollable information, data outliers and missing data. Each feature plays its own role and the need is to make them count equally while pre-processing the data.

DATA CLEANING:

The major part of data pre-processing is about correcting, repairing, and removing incorrect and

irrelevant data with the set dataset is done. First of all, we filtered out all the irrelevant and incorrect components that were there in the dataset we, such as, null values. Figure 5. step. 1: get utterances which contains null values in the dataset.

```

: #DATA_PREPROCESSING
crime_data.isnull().sum()

: TYPE          0
YEAR           0
MONTH          0
DAY            0
HOUR           0
MINUTE         0
HUNDRED_BLOCK 13
NEIGHBOURHOOD 0
X              0
Y              0
Latitude       0
Longitude      0
dtype: int64

```

Figure 5.1: Null values in dataset

Initially by declaring naming as crime data variable we able to analyse it with the help of this variable. Further, we zero in on all the null values present in the dataset and derive a new variable crime_data_1 which stashes all the imperative details pertaining to our project like day, month, hour, year etc. So we will be keeping only the significant values in our new variable and missing all the useless impurities thereby making our dataset more effective and refined for crime prediction. Figure 5. Aberg has the crime_data_1 initialization as the second value.

```

|: # getting the data of columns year,month,date,hour,neighbourhood
# which will be used further
crime_data_1=crime_data[['YEAR','MONTH','DAY','HOUR','NEIGHBOURHOOD']]
crime_data_1.shape

|: (474028, 5)

```

Figure 5.2: crime_data_1 initialized

DATA TRANSFORMATION:

The first stage of data cleaning had brought some changes in the dataset itself but data transformation would imply a thorough data format transformation hence you will be able to analyze your dataset better. It under the user data is made more homogeneous and adioninzaibly into normal range that can be compared safer.

In our data preprocessing converted data into a specific format such as by sorting the data by

date-time and also we removed duplicates from the new dataset(`crime_data_1`) which formed during data cleaning.

```
# Sort by date-time and removing duplicates
crime_data_1=crime_data_1.sort_values(by='Date-Time')
crime_data_1=crime_data_1.drop_duplicates()

crime_data_1.head()
```

Figure 5.3: Saving the sorted records and removing those with repetitive size.

]:

	YEAR	MONTH	DAY	HOUR	Arbutus-Ridge	Downtown	Dunbar-Southlands	Fairview	Grandview-Woodland	Hastings-Sunrise	...	Oakridge	Renfrew-Collingwood	Riley Park	Shaughnessy	South Cambie	Strathcona	Su
Date-Time																		
2004-01-01	2004	1	1	0.0	0	1	0	0	0	0	...	0	0	0	0	0	0	0
2004-01-01	2004	1	1	0.0	0	0	0	0	0	0	...	0	0	0	0	0	0	0
2004-01-01	2004	1	1	0.0	0	0	0	0	0	0	...	0	0	0	0	0	0	0
2004-01-01	2004	1	1	0.0	0	0	0	0	0	0	...	0	0	0	0	0	0	0
2004-01-01	2004	1	1	0.0	0	0	0	0	0	0	...	0	0	0	0	0	0	0

5 rows × 26 columns

Figure5.4: Data received after sorting the data and removing the duplicates from the dataset.

DATA REDUCTION

In other words, to enable us to process the data fast we cut it down so that in no time we can display the results. Moreover, there are problems to run models on very big dataset machines, and not every machine can do.

There you can see the duplicates in the figure 5 or use the link below. 4 that gave our data an added relational angle thus making analysis reduced by much and also less time consuming.

CHAPTER 6: MODEL MAKING

To-date, we have validated and cleaned the dataset and now we are ready with the finalized data which will be used as input for this project. First, we only had a dataset which had the statistics of different criminal activities in Vancouver for 15 years. The only null values after it was discarded and we also deleted all the duplicates. While crime prediction would be viable in terms of the practicality, then we will have to apply more databases. Data set bias, is only applicable when scientists are dealing with networks which has input data. In the project, we will deal with five neural networks which can take different parameters as inputs and their outputs purposes will be separated by different cases.

Now regarding this project there will be the application of feed –forward neural networks. This involves multi-layer perceptron. Unlike our initial intentions; There will be no application of a back-propagation operative for our method of progression; As to avoid the On learning model re-checking itself. This project aims to explain how the crime is going to be forecasted with the way of which we are going to do with the help of fedforward neural network. This network might fall under the same aspect of deep neural network since it has more than two hidden layers.

While other neural networks are actually quite complex and take longer to train than a deep neural network is comparatively easier to train and thus quicker. They are actually the highly sophisticated tools in replacing feature engineering to a greater extent; they help in training over large amounts of data. This available project includes criminal cases and also the attention to crime and spatial-temporal characteristics of crime such as location and time of day is also addressed. Again, the reality that deep neural networks can execute decisions from thousands of pounds of information make them seem like the most qualified neural nets applied in crime prediction in this fashion.

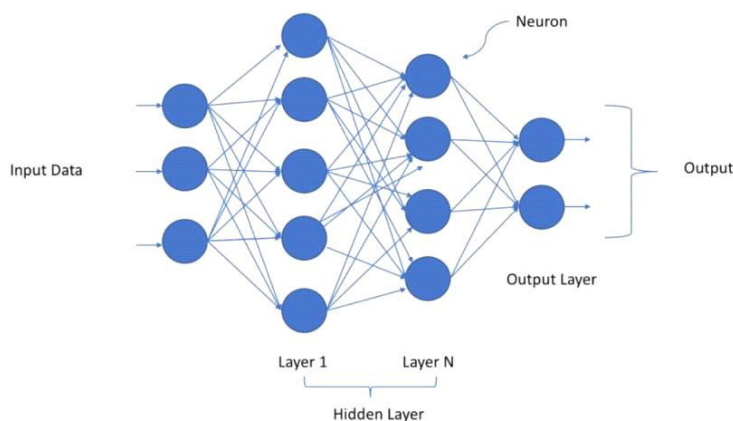


Figure 6.1: Deep neural network

Network 1

This is our primary network in which we will first attempt to model crime regression without any advanced techniques. Among these networks, we will apply the final dataset which we put together behind data visualization and data pre-processing steps. Lastly we are going to take data dataset which contains the information on the distance between the graffiti and the drinking fountain. We are doing so because we'd like to approach the issue practically and try to get the highest precision. The second goal will be to provide a user-friendly output which is understandable even by an average person and requires neither machine learning nor data science

In graffiti dataset there are 8508 points that provide the data. These points mark where each tag is on today's Vancouver map. This dataset contains the following columns: This dataset contains the following columns:

Latitude

Longitude

Map ID

Latitude

Longitude

Name

Location

Maintainer

In Operation

Pet Friendly

Photo

Following are the input parameters for network 1:

Year

Month

Day

Latitude

Longitude

Distance to Graffiti

Distance to drinking fountain

Fountain distance is another data set that exactly is being used for this neural network. Such dataset includes 241+ drinking fountains that are placed in all the areas of the province. This dataset contains the following columns: This dataset contains the following columns:

The next figure in this graph represents the accuracy and loss of the network as it was being trained.

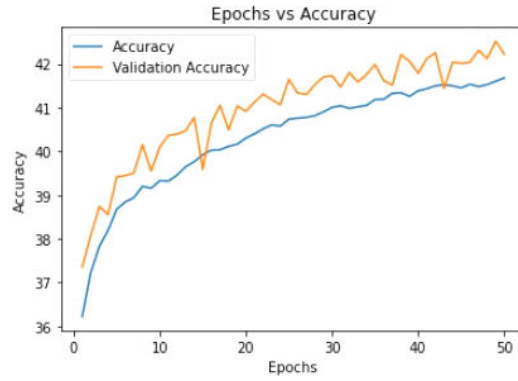


Figure 6.2: Epochs vs. Accuracy for network 1

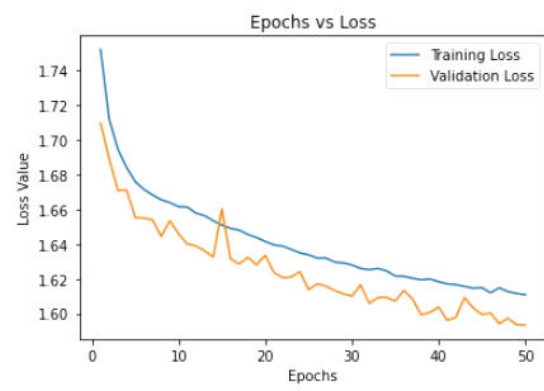


Figure 6.3: Epochs vs. Loss for network 1

```

Epoch 1/50
2017/2017 [=====] - 10s 5ms/step - loss: 1.7518 - accuracy: 0.3622 - val_loss: 1.7095 - val_accuracy: 0.3735
Epoch 2/50
2017/2017 [=====] - 10s 5ms/step - loss: 1.7119 - accuracy: 0.3722 - val_loss: 1.6892 - val_accuracy: 0.3808
Epoch 3/50
2017/2017 [=====] - 11s 5ms/step - loss: 1.6945 - accuracy: 0.3783 - val_loss: 1.6707 - val_accuracy: 0.3874
Epoch 4/50
2017/2017 [=====] - 11s 5ms/step - loss: 1.6840 - accuracy: 0.3819 - val_loss: 1.6711 - val_accuracy: 0.3855
Epoch 5/50
2017/2017 [=====] - 11s 6ms/step - loss: 1.6759 - accuracy: 0.3867 - val_loss: 1.6552 - val_accuracy: 0.3941
Epoch 6/50
2017/2017 [=====] - 12s 6ms/step - loss: 1.6714 - accuracy: 0.3884 - val_loss: 1.6549 - val_accuracy: 0.3944
Epoch 7/50
2017/2017 [=====] - 13s 6ms/step - loss: 1.6682 - accuracy: 0.3894 - val_loss: 1.6539 - val_accuracy: 0.3951
Epoch 8/50
2017/2017 [=====] - 14s 7ms/step - loss: 1.6654 - accuracy: 0.3920 - val_loss: 1.6443 - val_accuracy: 0.4016
Epoch 9/50
2017/2017 [=====] - 15s 7ms/step - loss: 1.6638 - accuracy: 0.3916 - val_loss: 1.6534 - val_accuracy: 0.3955
Epoch 10/50
2017/2017 [=====] - 14s 7ms/step - loss: 1.6615 - accuracy: 0.3933 - val_loss: 1.6458 - val_accuracy: 0.4010
Epoch 11/50
2017/2017 [=====] - 15s 7ms/step - loss: 1.6613 - accuracy: 0.3932 - val_loss: 1.6400 - val_accuracy: 0.4036
Epoch 12/50
2017/2017 [=====] - 15s 7ms/step - loss: 1.6577 - accuracy: 0.3945 - val_loss: 1.6389 - val_accuracy: 0.4040
Epoch 13/50
2017/2017 [=====] - 15s 7ms/step - loss: 1.6563 - accuracy: 0.3965 - val_loss: 1.6362 - val_accuracy: 0.4047
Epoch 14/50
2017/2017 [=====] - 16s 8ms/step - loss: 1.6534 - accuracy: 0.3976 - val_loss: 1.6324 - val_accuracy: 0.4078
Epoch 15/50
2017/2017 [=====] - 16s 8ms/step - loss: 1.6509 - accuracy: 0.3992 - val_loss: 1.6603 - val_accuracy: 0.3959
Epoch 16/50
2017/2017 [=====] - 16s 8ms/step - loss: 1.6480 - accuracy: 0.4003 - val_loss: 1.6511 - val_accuracy: 0.4065

```

Figure 6.4: Epoch cycles of network 1

This particular network gives us a precision score of 42%. Where temperature increases, the growth process is 86% faster than the test loss of 1. 61. In this networking system we mobile 50 epoch cycles. For the first session about 36% accuracy which got improved to 42% in the next cycleAt the 50th epoch 86% accuracy value is the result.

We have achieved accuracy of 42% which is not fabulous but that is mostly due to the current network of mine. It will help to inject the output the way we want it to be. The annexed figure is output of this system which provides al devices with the information they need as our job is not completed yet and need to work on the accuracy of this network.

```

1/1 [=====] - 0s 28ms/step
At 0 hour:
Probability of Break and Enter Commercial: 13%
Probability of Break and Enter Residential/Other: 4%
Probability of Mischief: 24%
Probability of Other Theft: 1%
Probability of Theft from Vehicle: 41%
Probability of Theft of Bicycle: 7%
Probability of Theft of Vehicle: 3%
Probability of Vehicle Collision or Pedestrian Struck (with Fatality): 0%
Probability of Vehicle Collision or Pedestrian Struck (with Injury): 2%
1/1 [=====] - 0s 25ms/step
At 5 hour:
Probability of Break and Enter Commercial: 23%
Probability of Break and Enter Residential/Other: 6%
Probability of Mischief: 24%
Probability of Other Theft: 1%
Probability of Theft from Vehicle: 31%
Probability of Theft of Bicycle: 4%
Probability of Theft of Vehicle: 2%
Probability of Vehicle Collision or Pedestrian Struck (with Fatality): 0%
Probability of Vehicle Collision or Pedestrian Struck (with Injury): 3%
1/1 [=====] - 0s 19ms/step
At 10 hour:
Probability of Break and Enter Commercial: 3%
Probability of Break and Enter Residential/Other: 12%
Probability of Mischief: 15%
Probability of Other Theft: 3%
Probability of Theft from Vehicle: 43%
Probability of Theft of Bicycle: 12%
Probability of Theft of Vehicle: 4%
Probability of Vehicle Collision or Pedestrian Struck (with Fatality): 0%
Probability of Vehicle Collision or Pedestrian Struck (with Injury): 4%
1/1 [=====] - 0s 21ms/step
At 15 hour:
Probability of Break and Enter Commercial: 3%
Probability of Break and Enter Residential/Other: 9%
Probability of Mischief: 14%
Probability of Other Theft: 8%
Probability of Theft from Vehicle: 44%
Probability of Theft of Bicycle: 12%
Probability of Theft of Vehicle: 4%
Probability of Vehicle Collision or Pedestrian Struck (with Fatality): 0%
Probability of Vehicle Collision or Pedestrian Struck (with Injury): 2%
1/1 [=====] - 0s 17ms/step
At 20 hour:
Probability of Break and Enter Commercial: 3%
Probability of Break and Enter Residential/Other: 8%
Probability of Mischief: 12%
Probability of Other Theft: 3%
Probability of Theft from Vehicle: 51%
Probability of Theft of Bicycle: 13%
Probability of Theft of Vehicle: 5%
Probability of Vehicle Collision or Pedestrian Struck (with Fatality): 0%
Probability of Vehicle Collision or Pedestrian Struck (with Injury): 1%

```

Figure 6.5: Output of network 1

This explainable output features slang and dialects, and I will explain the context around the words. With this precision, the network is having problems processing data faster. The network that we have created had given us more power and the sense of accomplishment that one actually can fulfill his ambition by himself. We can conclude that our project is moving in the right direction as it is the following of the mentioned route. It is evident by theft from vehicles, for

example, that its percentage share varies accordingly depending on time. In 15 hours the percentage share was 44 while in the next 20 hours it was 51% which is practically true. Hence, we concluded that we are enjoyably immersed in this work and the model is also really getting a grip and work towards the right path which we can learn even more from. The model can differentiate street crimes and will know that the 20 hour theft is more common than the type of vehicle collision at 1%. On a more negative note, there is an increased possibility of vehicles colliding at 15 hours. The model has proved its understanding of the data already and it will be able to identify much better. Now we have to try to improve the accuracy of our model, by designing new layers and changing the learning parameters.

```

1/1 [-----] - 8s 28ms/step
At 0 hour:
Probability of Break and Enter Commercial: 13%
Probability of Break and Enter Residential/Other: 4%
Probability of Mischief: 24%
Probability of Other Theft: 1%
Probability of Theft from Vehicle: 41%
Probability of Theft of Bicycle: 7%
Probability of Theft of Vehicle: 3%
Probability of Vehicle Collision or Pedestrian Struck (with Fatality): 6%
Probability of Vehicle Collision or Pedestrian Struck (with Injury): 2%
1/1 [-----] - 8s 25ms/step
At 5 hour:
Probability of Break and Enter Commercial: 23%
Probability of Break and Enter Residential/Other: 6%
Probability of Mischief: 24%
Probability of Other Theft: 1%
Probability of Theft from Vehicle: 31%
Probability of Theft of Bicycle: 4%
Probability of Theft of Vehicle: 2%
Probability of Vehicle Collision or Pedestrian Struck (with Fatality): 6%
Probability of Vehicle Collision or Pedestrian Struck (with Injury): 3%
1/1 [-----] - 8s 19ms/step
At 10 hour:
Probability of Break and Enter Commercial: 3%
Probability of Break and Enter Residential/Other: 12%
Probability of Mischief: 15%
Probability of Other Theft: 3%
Probability of Theft from Vehicle: 43%
Probability of Theft of Bicycle: 12%
Probability of Theft of Vehicle: 4%
Probability of Vehicle Collision or Pedestrian Struck (with Fatality): 6%
Probability of Vehicle Collision or Pedestrian Struck (with Injury): 4%
1/1 [-----] - 8s 21ms/step
At 15 hour:
Probability of Break and Enter Commercial: 3%
Probability of Break and Enter Residential/Other: 9%
Probability of Mischief: 14%
Probability of Other Theft: 8%
Probability of Theft from Vehicle: 44%
Probability of Theft of Bicycle: 12%
Probability of Theft of Vehicle: 4%
Probability of Vehicle Collision or Pedestrian Struck (with Fatality): 6%
Probability of Vehicle Collision or Pedestrian Struck (with Injury): 2%
1/1 [-----] - 8s 17ms/step
At 20 hour:
Probability of Break and Enter Commercial: 3%
Probability of Break and Enter Residential/Other: 4%
Probability of Mischief: 12%
Probability of Other Theft: 3%
Probability of Theft from Vehicle: 51%
Probability of Theft of Bicycle: 1%
Probability of Theft of Vehicle: 5%
Probability of Vehicle Collision or Pedestrian Struck (with Fatality): 6%
Probability of Vehicle Collision or Pedestrian Struck (with Injury): 1%

```

Figure 6.6: Output of network 1 with labeling

Network 2

This will be our model, and here, we will strive to bring our project accuracy to perfection. Thus far, we have achieved significant progress in our collaboration by generating the required data in the given format. In network 2 we were focusing on crime type forecast which may occur at any other place and time. However, the model that we will be utilizing to predict crime in the community is different from the one that is deployed for the entire city.

The network under discussion will be using the dataset that had been determined final in the above-mentioned section. The processed data is fed into all networks and this makes it a perfect fit for the testing of all networks.

Another point in the data we have used the column for crime that creates the column in the data. This column simply shows if a crime did or did not report. This could refer to anything from traffic accidents and acts of violence, to natural disasters as well as uneventful days. If such crime has been committed then its value will be 1 but if it not has been Reworked: If so it is true that this crime a mess, value will be 1, but it its not the case then no, because 1 value will not be true. if a magnitude is 0 then the value is also 0. Beside, when there is no crime at a certain hour, we have included this hour also in the data set, and in opposite, the value against it should be 0. Let us consider the fact it is not possible for any crime to be committed at 5 hours, which means we have added that value with a 0. The method of this manner can be a way to enhance our model's accuracy.

Following are the input parameters for this network:Following are the input parameters for this network:

Year

Month

Day

Hour

Neighborhood

We expect this network to give us the probability of crime occurring.

The following plots show the accuracy and loss of the model when it was under training.

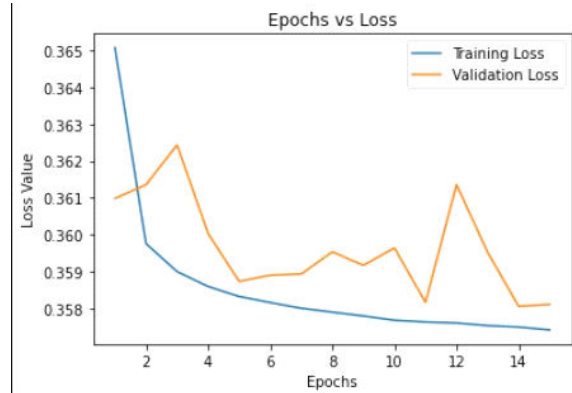


Figure 6.7: Epoch vs. Loss for network 2

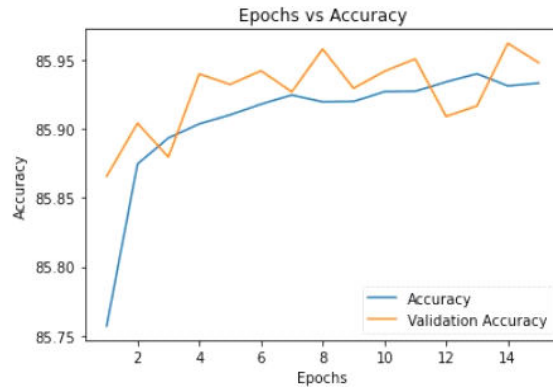


Figure 6.8: Epoch vs. Accuracy for network 2

We achieve this rate of accuracy of 85% and the test loss is 0 for the connection. 35. Furthermore of this network, we used a training process which consisted of 15 epoch cycles. For first cycle our accuracy at 85 percent. Increased from 76% to 85% which the real rate of inflation is now higher than the targeted one. By the end of the 93rd epoch cycle, we achieved an accuracy of 93% in our trading strategy. For this particular neural network we select a 15-cycles mode since we strongly believe that it is able to improve our accuracy and besides, the previous tests assured us that this could work too. Through 50 training cycles, the time consumed are longer than expected. But it is useful when the model begins a very low-accuracy rate. The difference between them and others is that those people are not connected. It started with 85. 76% which is super fantastic.

```
Epoch 1/15
3365/3365 [=====] - 37s 11ms/step - loss: 0.3651 - accuracy: 0.8576 - val_loss: 0.3610 - val_accuracy: 0.8587
Epoch 2/15
3365/3365 [=====] - 45s 13ms/step - loss: 0.3598 - accuracy: 0.8587 - val_loss: 0.3614 - val_accuracy: 0.8590
Epoch 3/15
3365/3365 [=====] - 47s 14ms/step - loss: 0.3590 - accuracy: 0.8589 - val_loss: 0.3624 - val_accuracy: 0.8588
Epoch 4/15
3365/3365 [=====] - 47s 14ms/step - loss: 0.3586 - accuracy: 0.8590 - val_loss: 0.3600 - val_accuracy: 0.8594
Epoch 5/15
3365/3365 [=====] - 47s 14ms/step - loss: 0.3583 - accuracy: 0.8591 - val_loss: 0.3587 - val_accuracy: 0.8593
Epoch 6/15
3365/3365 [=====] - 49s 15ms/step - loss: 0.3582 - accuracy: 0.8592 - val_loss: 0.3589 - val_accuracy: 0.8594
Epoch 7/15
3365/3365 [=====] - 46s 14ms/step - loss: 0.3580 - accuracy: 0.8592 - val_loss: 0.3589 - val_accuracy: 0.8593
Epoch 8/15
3365/3365 [=====] - 45s 13ms/step - loss: 0.3579 - accuracy: 0.8592 - val_loss: 0.3595 - val_accuracy: 0.8596
Epoch 9/15
3365/3365 [=====] - 47s 14ms/step - loss: 0.3578 - accuracy: 0.8592 - val_loss: 0.3592 - val_accuracy: 0.8593
Epoch 10/15
3365/3365 [=====] - 47s 14ms/step - loss: 0.3577 - accuracy: 0.8593 - val_loss: 0.3596 - val_accuracy: 0.8594
Epoch 11/15
3365/3365 [=====] - 47s 14ms/step - loss: 0.3576 - accuracy: 0.8593 - val_loss: 0.3582 - val_accuracy: 0.8595
Epoch 12/15
3365/3365 [=====] - 48s 14ms/step - loss: 0.3576 - accuracy: 0.8593 - val_loss: 0.3614 - val_accuracy: 0.8591
Epoch 13/15
3365/3365 [=====] - 48s 14ms/step - loss: 0.3575 - accuracy: 0.8594 - val_loss: 0.3595 - val_accuracy: 0.8592
Epoch 14/15
3365/3365 [=====] - 48s 14ms/step - loss: 0.3575 - accuracy: 0.8593 - val_loss: 0.3581 - val_accuracy: 0.8596
Epoch 15/15
3365/3365 [=====] - 47s 14ms/step - loss: 0.3574 - accuracy: 0.8593 - val_loss: 0.3581 - val_accuracy: 0.8595
```

Figure 6.9: Epoch cycles of network 2

Now, coming to the output of this network. Following attached image shows the output of this network.

```

1/1 [=====] - 0s 19ms/step
Likelihood of crime at 0 hour: 26.921817660331726 %
1/1 [=====] - 0s 19ms/step
Likelihood of crime at 1 hour: 16.663280129432678 %
1/1 [=====] - 0s 17ms/step
Likelihood of crime at 2 hour: 10.911333560943604 %
1/1 [=====] - 0s 18ms/step
Likelihood of crime at 3 hour: 8.76353606581688 %
1/1 [=====] - 0s 20ms/step
Likelihood of crime at 4 hour: 7.493147999048233 %
1/1 [=====] - 0s 17ms/step
Likelihood of crime at 5 hour: 7.29091688990593 %
1/1 [=====] - 0s 18ms/step
Likelihood of crime at 6 hour: 7.475589215755463 %
1/1 [=====] - 0s 19ms/step
Likelihood of crime at 7 hour: 9.853264689445496 %
1/1 [=====] - 0s 21ms/step
Likelihood of crime at 8 hour: 13.913369178771973 %
1/1 [=====] - 0s 22ms/step
Likelihood of crime at 9 hour: 14.788274466991425 %
1/1 [=====] - 0s 19ms/step
Likelihood of crime at 10 hour: 15.107938647270203 %
1/1 [=====] - 0s 21ms/step
Likelihood of crime at 11 hour: 15.600347518920898 %
1/1 [=====] - 0s 20ms/step
Likelihood of crime at 12 hour: 16.152216494083405 %
1/1 [=====] - 0s 19ms/step
Likelihood of crime at 13 hour: 16.944578289985657 %
1/1 [=====] - 0s 22ms/step
Likelihood of crime at 14 hour: 18.922872841358185 %
1/1 [=====] - 0s 24ms/step
Likelihood of crime at 15 hour: 22.757135331630707 %
1/1 [=====] - 0s 21ms/step
Likelihood of crime at 16 hour: 27.94967293739319 %
1/1 [=====] - 0s 21ms/step
Likelihood of crime at 17 hour: 31.555747985839844 %
1/1 [=====] - 0s 18ms/step
Likelihood of crime at 18 hour: 31.043463945388794 %
1/1 [=====] - 0s 18ms/step
Likelihood of crime at 19 hour: 31.124475598335266 %
1/1 [=====] - 0s 21ms/step
Likelihood of crime at 20 hour: 31.099167466163635 %
1/1 [=====] - 0s 21ms/step
Likelihood of crime at 21 hour: 30.980491638183594 %
1/1 [=====] - 0s 19ms/step
Likelihood of crime at 22 hour: 30.763107538223267 %
1/1 [=====] - 0s 19ms/step
Likelihood of crime at 23 hour: 30.543339252471924 %

```

Figure 6.10: Output of network 2

This is our anticipated effect that was the main goal of our efforts. This statistics very clearly indicate to the predisposition to commit crimes on certain hour of the day. The crime rate at CR shows a 7% probability going along with hour 4The original 11 fell down to 5, correspondingly reaching a higher volume of 15. 10 at 10 hour. The night-time security cameras captured that the crime rose to 30%76. By this, we can assume to our model that all this actually happens in the real life and everyday life. We have high increased chances of victimization as time goes late than day does. It can be observed from the

model that we have hashed present in the image below.

```
1/1 [-----] - 0s 19ms/step
Likelihood of crime at 0 hour: 26.921817660331726 %
1/1 [-----] - 0s 19ms/step
Likelihood of crime at 1 hour: 16.663288129432678 %
1/1 [-----] - 0s 17ms/step
Likelihood of crime at 2 hour: 10.911333560943604 %
1/1 [-----] - 0s 18ms/step
Likelihood of crime at 3 hour: 8.76353606581688 %
1/1 [-----] - 0s 28ms/step
Likelihood of crime at 4 hour: 7.403147990048233 %
1/1 [-----] - 0s 17ms/step
Likelihood of crime at 5 hour: 7.29091688990593 %
1/1 [-----] - 0s 18ms/step
Likelihood of crime at 6 hour: 7.47598215755463 %
1/1 [-----] - 0s 19ms/step
Likelihood of crime at 7 hour: 9.853264689445496 %
1/1 [-----] - 0s 21ms/step
Likelihood of crime at 8 hour: 13.913369178773973 %
1/1 [-----] - 0s 22ms/step
Likelihood of crime at 9 hour: 14.780274466991425 %
1/1 [-----] - 0s 19ms/step
Likelihood of crime at 10 hour: 15.107938647270203 %
1/1 [-----] - 0s 23ms/step
Likelihood of crime at 11 hour: 15.600347518920868 %
1/1 [-----] - 0s 28ms/step
Likelihood of crime at 12 hour: 16.152216494083405 %
1/1 [-----] - 0s 19ms/step
Likelihood of crime at 13 hour: 16.944578289985657 %
1/1 [-----] - 0s 22ms/step
Likelihood of crime at 14 hour: 18.922872841358185 %
1/1 [-----] - 0s 24ms/step
Likelihood of crime at 15 hour: 22.757135331630707 %
1/1 [-----] - 0s 21ms/step
Likelihood of crime at 16 hour: 27.94967293739319 %
1/1 [-----] - 0s 21ms/step
Likelihood of crime at 17 hour: 31.555747985839844 %
1/1 [-----] - 0s 18ms/step
Likelihood of crime at 18 hour: 31.843463945388794 %
1/1 [-----] - 0s 18ms/step
Likelihood of crime at 19 hour: 31.124475508335266 %
1/1 [-----] - 0s 21ms/step
Likelihood of crime at 20 hour: 31.099167466163635 %
1/1 [-----] - 0s 21ms/step
Likelihood of crime at 21 hour: 30.988491638183594 %
1/1 [-----] - 0s 19ms/step
Likelihood of crime at 22 hour: 30.763107538223267 %
1/1 [-----] - 0s 19ms/step
Likelihood of crime at 23 hour: 30.543339252471924 %
```

Figure 6.11: Output of network 2 with labeling.

Beyond doubt that is where law enforcement have undoubtedly been in a position to reign. It is not necessary to really believe that this prediction can perhaps come true, but it is necessary to install beforehand certain safety measures according to this prediction. Besides, our machine read the information and therefore, she demonstrated her abilities. And again we will use the model by providing varied data along with the input parameters to assess whether there is any alteration in the subsequent prophesy or not.

Network 2.1

This network is same as the network 2 but in this we will be working with new input parameters .

Our interest is to do things further as the crime is dependent on several factors so we believe that the input which we had in mind will be incorporated in upcoming drives.

Following are the input parameters of this network:

Year

Month

Day

Hour

Minute

Latitude

Longitude

Distance from nearest graffiti

Distance from nearest drinking fountain.

Following plots show the accuracy and loss of this network with respect to epoch cycle.

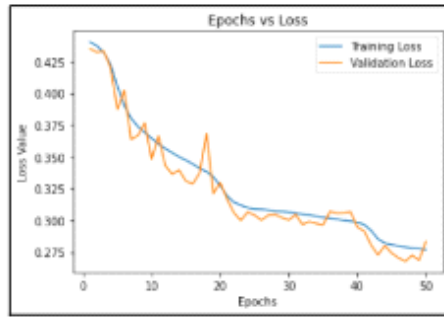


Figure 6.12: Epoch vs Loss for network 2.1

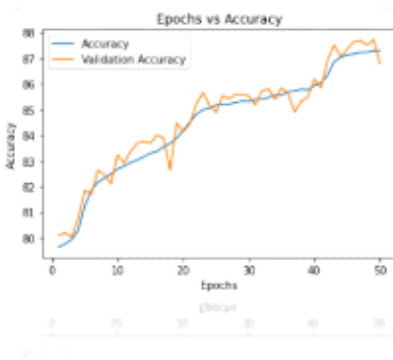


Figure 6.13: Epoch vs Accuracy for network 2.1

Figure 1 is an illustration of how the network differs from network 2 where it is evident that the output of the network is different compared to network 2. In the range of these outputs it is from 77 and up to 99.

```

1/1 [=====] - 0s 33ms/step
Likelihood of crime at 0 hour: 98.38404655456543 %
1/1 [=====] - 0s 40ms/step
Likelihood of crime at 1 hour: 97.9418933391571 %
1/1 [=====] - 0s 20ms/step
Likelihood of crime at 2 hour: 88.66969347000122 %
1/1 [=====] - 0s 27ms/step
Likelihood of crime at 3 hour: 78.06049585342407 %
1/1 [=====] - 0s 25ms/step
Likelihood of crime at 4 hour: 78.379446268808167 %
1/1 [=====] - 0s 33ms/step
Likelihood of crime at 5 hour: 84.35927033424377 %
1/1 [=====] - 0s 31ms/step
Likelihood of crime at 6 hour: 91.41652584075928 %
1/1 [=====] - 0s 19ms/step
Likelihood of crime at 7 hour: 92.79564619064331 %
1/1 [=====] - 0s 16ms/step
Likelihood of crime at 8 hour: 93.68543028831482 %
1/1 [=====] - 0s 39ms/step
Likelihood of crime at 9 hour: 94.77003216743469 %
1/1 [=====] - 0s 25ms/step
Likelihood of crime at 10 hour: 95.76441645622253 %
1/1 [=====] - 0s 22ms/step
Likelihood of crime at 11 hour: 96.50751948356628 %
1/1 [=====] - 0s 41ms/step
Likelihood of crime at 12 hour: 97.05377221107483 %
1/1 [=====] - 0s 22ms/step
Likelihood of crime at 13 hour: 97.48725295066833 %
1/1 [=====] - 0s 19ms/step
Likelihood of crime at 14 hour: 97.8569507598877 %
1/1 [=====] - 0s 29ms/step
Likelihood of crime at 15 hour: 98.18381071090698 %
1/1 [=====] - 0s 19ms/step
Likelihood of crime at 16 hour: 98.47477078437805 %
1/1 [=====] - 0s 30ms/step
Likelihood of crime at 17 hour: 98.7312376499176 %
1/1 [=====] - 0s 34ms/step
Likelihood of crime at 18 hour: 98.9533543586731 %
1/1 [=====] - 0s 19ms/step
Likelihood of crime at 19 hour: 99.14187788963318 %
1/1 [=====] - 0s 37ms/step
Likelihood of crime at 20 hour: 99.29876327514648 %
1/1 [=====] - 0s 22ms/step
Likelihood of crime at 21 hour: 99.42710399627686 %
1/1 [=====] - 0s 37ms/step
Likelihood of crime at 22 hour: 99.5306670665741 %
1/1 [=====] - 0s 21ms/step
Likelihood of crime at 23 hour: 99.61342215538025 %
1/1 [=====] - 0s 35ms/step
Likelihood of crime at 24 hour: 99.67915415763855 %

```

Figure 6.14: Output of network 2.1

In the above case, we can view that the values of the output oscillating with time on the high side. I infer that the probability of crime at midnight is 98%. 3 divided by 4 equals 78, thus the result is 3/4 which can be further reduced to 78. 37 at hour 4. In the day time those odds are 95% confirm again. 7 at the end of 10th hour, and it stands now 99. 42. This figure is a good example of the topic in discussions.

Network 2.2

On the other hand, this one is also same as network 2 having different input values. For this particular project I will also be using a Google trends dataset. This documentation describes the volume of bloody word crime search within the city of Vancouver. We decided to use this dataset as the main one because it has been discovered that crime depends to some extent on the volume

of queries on Google. As proof of this, we will utilize a set of data.

Following are the input parameters of this network:

Year

Month

Day

Hour

Minute

Latitude

Longitude

Distance from nearest graffiti

Distance from nearest drinking fountain.

Google Trend data

Following plots show the accuracy and loss of this network with respect to epoch cycle.

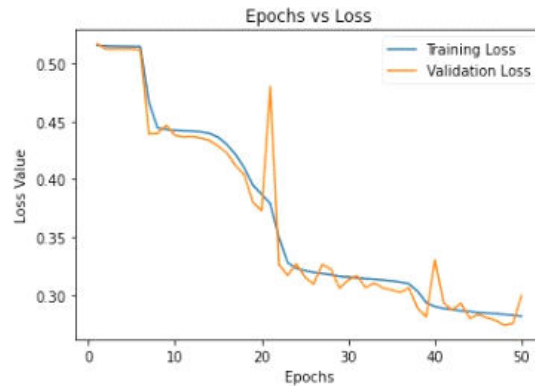


Figure 6.16: Epoch vs Loss for network 2.2

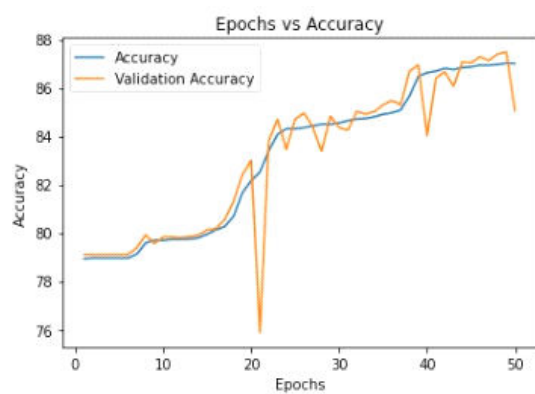


Figure 6.17: Epoch vs Accuracy for network 2.2

Epochs for training of our network are 50. In the beginning we noted score of 78% and then it got better to 87%. This particular setup showed Google trend data is in fact effecting the crime rate. Looking for criminal activities is not such a regular practice and therefore the authorities have taken upon them the task of monitoring anyone who may search for the same on Google. The pictures below illustrates what our model produces and as from the output we can realize that it's totally different from what we had before. For the network 3 we possess the probabilities in the interval of 30 to 50% and in the network 2 the range alters to 89% to 99% values. What is more, there is nothing that depends on us, but we can see the data that we received and we mostly check it to know if we are not mistaken and the prediction is right.

```

1/1 [=====] - 0s 76ms/step
Likelihood of crime at 0 hour: 99.46082830429077 %
1/1 [=====] - 0s 59ms/step
Likelihood of crime at 1 hour: 96.39050960540771 %
1/1 [=====] - 0s 69ms/step
Likelihood of crime at 2 hour: 89.60691690444946 %
1/1 [=====] - 0s 88ms/step
Likelihood of crime at 3 hour: 87.88430094718933 %
1/1 [=====] - 0s 98ms/step
Likelihood of crime at 4 hour: 92.54114031791687 %
1/1 [=====] - 0s 66ms/step
Likelihood of crime at 5 hour: 96.70429825782776 %
1/1 [=====] - 0s 75ms/step
Likelihood of crime at 6 hour: 97.59701490402222 %
1/1 [=====] - 0s 62ms/step
Likelihood of crime at 7 hour: 98.01601767539978 %
1/1 [=====] - 0s 93ms/step
Likelihood of crime at 8 hour: 98.4180748462677 %
1/1 [=====] - 0s 73ms/step
Likelihood of crime at 9 hour: 98.73809218406677 %
1/1 [=====] - 0s 67ms/step
Likelihood of crime at 10 hour: 98.94948601722717 %
1/1 [=====] - 0s 67ms/step
Likelihood of crime at 11 hour: 99.08435344696045 %
1/1 [=====] - 0s 80ms/step
Likelihood of crime at 12 hour: 99.17385578155518 %
1/1 [=====] - 0s 47ms/step
Likelihood of crime at 13 hour: 99.23633337020874 %
1/1 [=====] - 0s 60ms/step
Likelihood of crime at 14 hour: 99.28176403045654 %
1/1 [=====] - 0s 90ms/step
Likelihood of crime at 15 hour: 99.31581020355225 %
1/1 [=====] - 0s 72ms/step
Likelihood of crime at 16 hour: 99.34192895889282 %
1/1 [=====] - 0s 85ms/step
Likelihood of crime at 17 hour: 99.36236143112183 %
1/1 [=====] - 0s 62ms/step
Likelihood of crime at 18 hour: 99.37863945960999 %
1/1 [=====] - 0s 60ms/step
Likelihood of crime at 19 hour: 99.3918240070343 %
1/1 [=====] - 0s 69ms/step
Likelihood of crime at 20 hour: 99.40269589424133 %
1/1 [=====] - 0s 65ms/step
Likelihood of crime at 21 hour: 99.41179752349854 %
1/1 [=====] - 0s 71ms/step
Likelihood of crime at 22 hour: 99.41954016685486 %
1/1 [=====] - 0s 81ms/step
Likelihood of crime at 23 hour: 99.42622780799866 %
1/1 [=====] - 0s 100ms/step
Likelihood of crime at 24 hour: 99.43208694458008 %

```

Figure 6.18: Output of network 2.2

On the way to that network it really has a really high rate of crime at every hour but they vary throughout the hours. : 0 99 for 0 The first hours is . 46 which is far from 89% in the second step. 6 at hour 2. The expectation for a crime within 10 hours is 0. 98. The chance of crime at 09:At 45 the odds are 94 while at 11: 00 the odds 99. All these numbers are somewhat higher than the chances of crime at just 10 hours – 41 . This is where the discussion that follows comes in; a visual illustration is provided in form of a photo below.

It is on this therefore that we can be able to conclude and therefore state that it is possible to note

that the Google popularity data has some impacts on the crime and through that it is easier to be able to predict crime with more realism.

CHAPTER 7: CONCLUSION

The crime pattern of the city of Vancouver was retrieved from the last 15 years using various datasets and the crime pattern were created using two dataset approaches. First of all, the crime dataset was obtained from the open data portal of the city of Vancouver and using python language used to the same. The dataset was analyzed which enabled us to present the general rate of crime in various areas of Vancouver between 2003 and 2017 and especially how the crime rates changed in all the year under consideration regarding time of day, day of week and location/neighborhood. Meanwhile we were sure that it has any values for our goals. Having this in mind we can state that in case of events that happened and fact that we decided to remove the null values which is quite understandable lead to precision improvement in the results of data cleaning. In addition to this, we created data manipulation by ordering our data set by date/time. Doing this task consequently solely contributed to refining our common model to the one predicated upon an artificial neural network. With that this project was successful in showing the machine's point of view to map the crime with use of neural network. The accuracy level that the project achieved was 87 percentage, which is a high level of accuracy. The accuracy rate of our model was very high owing to its ability to learn the relationship between crime and affect and its effects on prediction. Unlike most we have something new and rather unique and I would even go as far as to say innovative in the way we are producing our crime predictions and give it a very practical application. So to find some patterns underneath the crime we used some datasets and we also modified the input parameters of the network to understand the crime.

CHAPTER 8: FUTURE SCOPE

The ideas of this project will be taken way forward. There are different aspects we can focus our efforts on such as network accuracy and using a wide range of datasets to predict crime. It is possible for us to develop more research on the ways on which crime is influenced and also include them as factors. Learning the technical progress of our project ,we department should

concentrate on the development of the frontend of the project ,so that people who know nothing about Python can also enter the project.

Predictive policing: Concept known as predictive policing utilizes data analytics and machine learning algorithms to forecast in which region the crime rate is high, and therefore, allocate manpower and other resources to control such crimes. One the many places ANNs can be used is in predictive analysis for crime patterns so the crimes can be promptly addressed.

The main role for these functionalities is driving the procedural tasks for such procedures and thus ensuring the accuracy of the results. Although failure rate of this system is still quite high, the system still enables the improvement process, though.

As a whole, can provide crime prediction models a wide range of future applications and getting better results through advancement of the algorithms of machine learning and data integration techniques can gain the accuracy and effectiveness of these models.

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