#### A MINI PROJECT REPORT

## CRIME RATE PREDICTION AND ANALYSIS USING MACHINE LEARNING

Submitted by

**S.ABHINAYA - 21TK1A6626** 

In partial fulfillment for the award of the degree of

**BACHELORS OF TECHNOLOGY** 

IN

ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

**Under the esteemed guidance of** 

Dr. G. Ranjith

Asst. Professor, Department of AI&ML



SVS GROUP OF INSTITUTIONS-SCHOOL OF ENGINEERING

DEPARTMENT OF ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

Bheemaram, Warangal 506015, TELANGANA

2024-2025

#### **SVS GROUP OF INSTITUTIONS**

#### DEPARTMENT OF ARTIFICIAL INTELLIGENCE & MACHINE LEARNING



#### **CERTIFICATE**

This is to certify that **S.ABHINAYA** -21TK1A6628 of the B tech has satisfactorily completed the dissertation work entitled "Crime Rate Prediction And Analysis Using Machine Learning" in the partial fulfillment of the requirements of the B. Tech degree during this academic year 2024-2025.

INTERNAL	<u>HOD(AIML)</u>	<u>PRINCIPAL</u>
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Asst. Professor	Asst. Professor	Dept of (AI&ML)
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DEPARTMENT OF COMPUTER SCIENCE&ENGINEERING SVS INSTITUTE OF TECHNOLOGY BHEEMARAM ,HANAMKONDA- 506015

ISO 9001:2008 CERTIFIED

DECLARATION BY THE CANDIDATE

I bearing the **S.ABHINAYA** H.T No 21TK1A6628, to hereby certify that the Project

Report entitled "CRIME RATE PREDICTION", under the guidance of Dr. G.RANJITH.

Department of CSE(AI&ML), SVS Institute of Technology & Science, Hanamkonda, submitted

in partial fulfillment of the requirements for the Award of the Degree of Master of Technology in

Artificial Intelligence & Machine Learning.

This is a record of Bonafide work carried out by me and the results embodied in this Project

Report has not been produced / copied from any source. The results embodied in this Project

Report have not been submitted to any other University or Institute for the Award of any other

Degree or Diploma.

PLACE: Hanamkonda

DATE: 30-01-25

**S.ABHINAYA - 21TK1A6628** 

III

#### DEPARTMENT OF COMPUTER SCIENCE&ENGINEERING SVS INSTITUTE OF TECHNOLOGY BHEEMARAM ,HANAMKONDA-506015



#### DECLARATION BY THE CANDIDATE

This is to certify that the Project Report entitled "CRIME RATE PREDICTION" being submitted by "S.ABHINAYA H.T No 21TK1A6628,in partial fulfillment of the requirements for the Award of the Degree of the Master of Technology in Artificial Intelligence & Machine Learning.is a record of Bonafide work carried out by him under my guidance.

The results of investigation enclosed in the report have been verified and found satisfactory. The results embodied in this thesis have not been submitted to any other University for the award of any degree or diploma.

Place:Hanamnonda

Date:30-01-25

Dr.G.RANJITH

Asst Professor & HOD

#### **ACKNOWLEDGMENT**

The completion of this project work gives me an opportunity to convey my gratitude to all those who helped me to complete the project successfully.

First, I gratefully acknowledge my deep sense of gratitude to Almighty for spiritual Guidance blessings shown to complete the Project. I thank my parents for unconditional support to improve myself throughout my life.

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S.ABHINAYA - 21TK1A6628

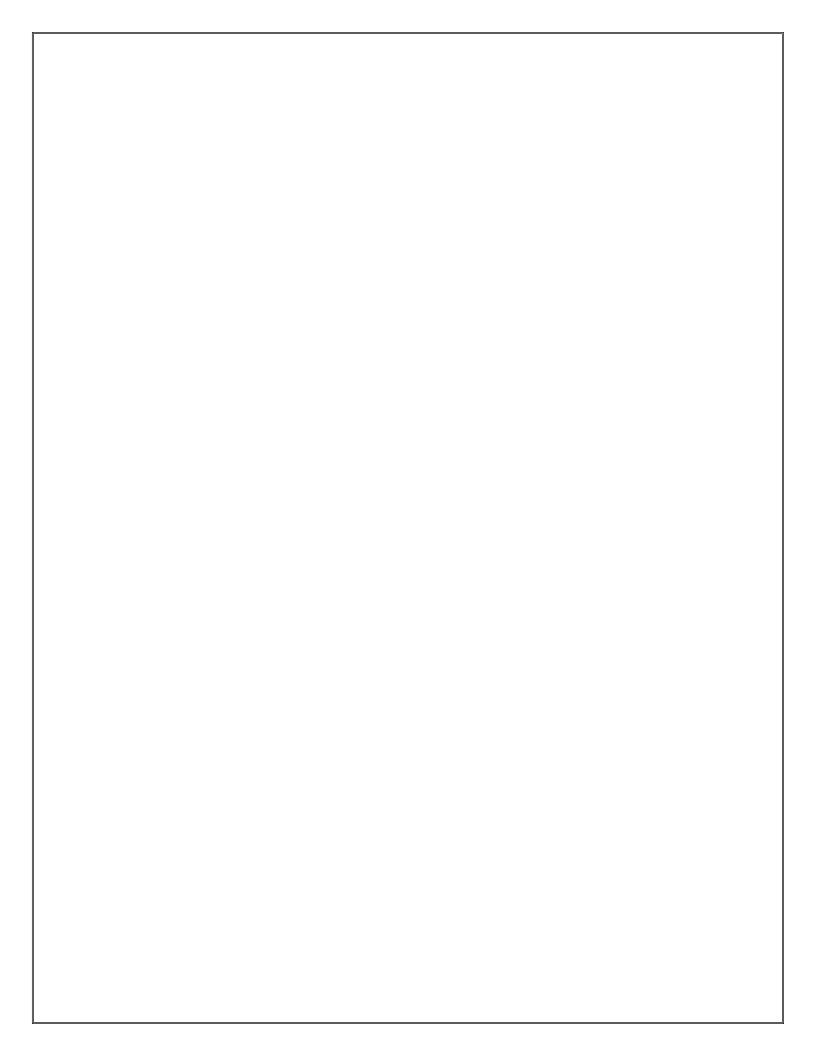
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#### **ABSTRACT**

Day by day crime data rate is increasing because the modern technologies and hi-tech methods are helps the criminals to achieving the illegal activities According to Crime Record Bureau crimes like burglary, arson have been increased while crimes like murder, sex, abuse, gang rap have been increased Crime data will be collected from various blogs, news and websites. The huge data is used as a record for creating a crime report database. The knowledge which is acquired from the data mining techniques will help in reducing crimes as it helps in finding the culprits faster and also the areas that are most affected by crime day by day crime data rate is increasing because the modern technologies and hitech methods are helps the criminals to achieving the illegal activities .According to Crime Record Bureau crimes like burglary, arson have been increased while crimes like murder, sex, abuse, gang rap have been increased.



# CHAPTER 1 INTRODUCTION 1

#### .1Purpose:

The purpose of crime rate prediction and analysis using machine learning is to leverage advanced Computational techniques to identify patterns, trends, and potential future occurrences of criminal activity. This approach enables law enforcement agencies to allocate resources more efficiently, enhance public safety, and develop proactive strategies to prevent crime. By analysing historical data and realtime inputs, machine learning models can provide valuable insights into high-risk areas, optimal patrol routes, and potential crime hotspots, thereby improving the effectiveness of crime prevention and intervention efforts.

#### 1.2Background of project:

crime rate prediction and analysis using machine learning stems from the growing need for innovative solutions to tackle the persistent issue of crime in urban environments. Traditional crime prevention methods, which often rely on reactive measures and historical crime data, are insufficient in addressing the dynamic and complex nature of criminal activities. With the advent of big data and machine learning technologies, there is an opportunity to harness vast amounts of data from various sources, such as police reports, social media, weather conditions, and demographic information, to build predictive models that can provide more accurate and timely insights into crime trends. Machine learning algorithms excel at detecting patterns and making predictions based on large datasets, which are often beyond the capability of manual analysis. By implementing these technologies, the project aims to transform raw data into actionable intelligence that can predict future crime hotspots, identify potential perpetrators, and optimize resource allocation for law enforcement agencies. This proactive approach not only enhances the efficiency of crime prevention strategies but also contributes to the overall safety and security of communities by enabling pre-emptive measures to thwart criminal activities before they occur

## 1.3 Scope of project:

Crime rate prediction and analysis using machine learning holds significant potential for improving public safety and resource allocation. By leveraging historical crime data and advanced algorithms, machine learning models can identify patterns and trends, enabling law enforcement agencies to predict future crime hotspots and times with greater accuracy. This proactive approach allows for optimized deployment of police resources, timely interventions, and better-informed policy decisions. Moreover, integrating socio-economic factors and real-time data can enhance the precision and effectiveness of these predictive models.

#### 1.4 Project Features:

1. Spatial

**Features:** Use geographic information to create features like distance to police stations, crime hot spots, and neighbourhood characteristics

2. Model

**Selection:** Implement and compare various machine learning algorithms.

3. Data

Collection: Gather historical crime data, socioeconomic data, weather data, and other relevant information.

4. Prediction and

Visualization: Generate predictions, create risk maps and dashboards, and provide actionable insight

## **SYSTEMREQUIREMENTS**

#### 2.1 Hardware Requirements:

- HDD 500 GB
- RAM 4 GB
- Processor intel i5
- Keyboard
- Mouse

#### 2.2 Software requirements:

#### **Frontend:**

JUPYTER

#### **Backend:**

• Python

#### **Operating System:**

• Windows 10

## 2.3 Existing System:

- 1. Data Mining Clustering
- 2. Naïve Baye
- 3. Spatial Analysis
- 4. Logistic Regression

## 2.3.1Drawbacks of existing system:

1. Data Quality and Bias: The accuracy of predictions heavily depends on the quality and completeness of historical crime data. Inconsistent, incomplete, or biased data can lead to flawed predictions and reinforce existing biases in policing.

#### 2. Privacy Concerns:

These systems often require access to vast amounts of personal and sensitive data, raising concerns about privacy and the potential for misuse of information.

#### 3. Over-policing:

Predictive models might lead to over-policing in certain areas, particularly those with higher recorded crime rates, potentially exacerbating community tensions and unfairly targeting specific demographics.

#### 4. Ethical Concerns:

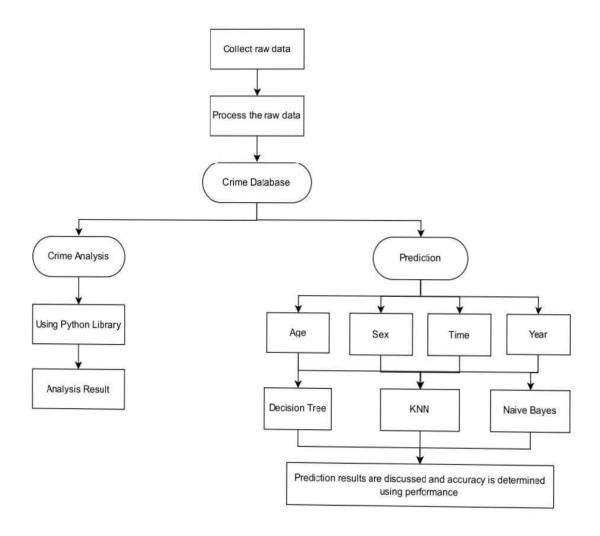
There are significant ethical concerns regarding the potential for machine learning systems to perpetuate systemic biases and inequalities present in the historical data used to train them.

#### **2.4 Proposed System:**

It consists of crime information like location description, type of crime, date, time, latitude, longitude. Before training the model data preprocessing will be done following this feature Neighbour selection and scaling will be done so that the accuracy obtained will be high. The K-Nearest (KNN) classification and various other algorithms (Decision Tree and Random Forest) will be tested for crime and propose one with better query-based use for training. Visualization of the dataset will be done in terms of graphical representation of many cases, for example at which time the crime rates are high or at which month the criminal activities are high. The sole purpose of this project is to give a just idea of how machine learning can be used by law enforcement agencies to detect, predict and involve crimes at a much faster rate and thus reduce the crime rate. This can be used in other states or countries depending upon the availability of the data set. We will be using the technique of machine learning and data science for crime prediction of crime data sets. The crime data is extracted from the official portal of police

## **SYSTEM DESIGN**

## 3. 1 System Architecture



## 3.2 UML Diagrams

## 3.2.1 Use case diagram

Use Case during requirement elicitation and analysis to represent the functionality of the system. Use case describes a function by the system that yields a visible result for an actor. The identification of actors and use cases result in the definitions of the boundary of the system i.e., differentiating the tasks

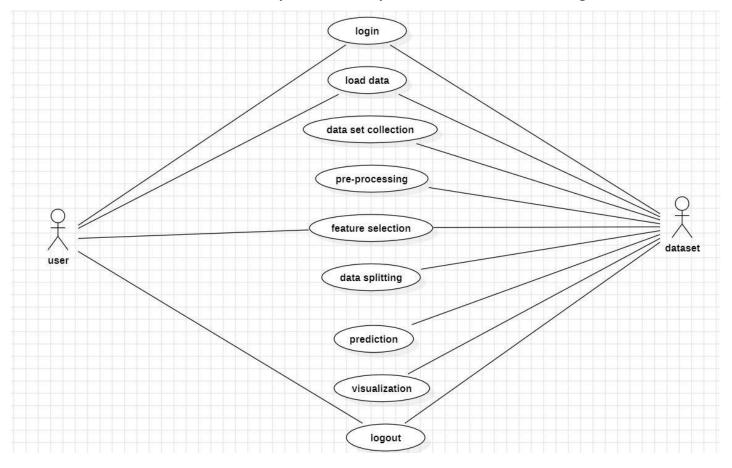


Fig 3.2.1 Use Case Diagram of CRPAML

#### 3.2.2 Class Diagram

Class diagrams model class structure and contents using design elements such as classes, packages and objects. Classes are composed of three things: name, attributes, and operations. Class diagram also display relationships such as containment, inheritance, association etc. The association relationship is most common relationship in a class diagram. The association shows the relationship between instances o

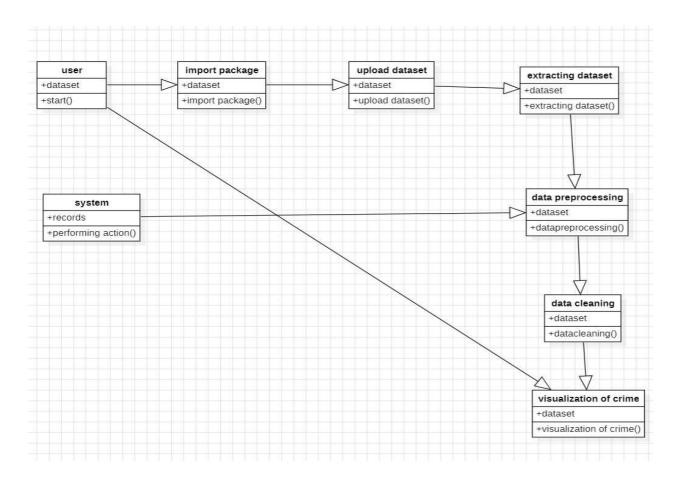


Fig 3.2.2 Class Diagram of CRPAML

#### 3.2.3 Sequence Diagram

Sequence diagram displays the time sequence of the objects participating in the interaction. This consists of the vertical dimension (time) and horizontal dimension (different objects). Objects: An object can be thought of as an entity that exists at a specified time and has a definite value, as well as a holder of identity. A sequence diagram depicts item interactions in chronological order. It illustrates the scenario's objects and classes, as well as the sequence of messages sent between them in order to carry out the scenario's functionality. In the Logical View of the system under development, sequence diagrams are often related with use case realizations. Event diagrams and event scenarios are other names for sequence diagrams. A sequence diagram depicts multiple processes or things that exist simultaneously as parallel vertical lines (lifelines), and the messages passed between them as horizontal arrows, in the order in which they occur. This enables for the graphical specification of simple runtime scenarios

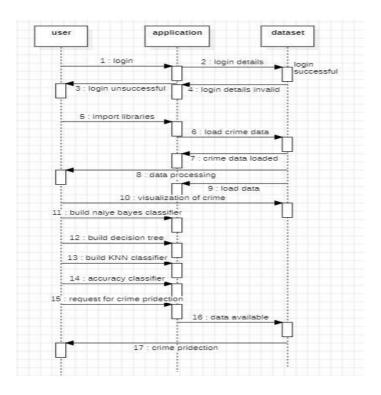


Fig 3.2.2 Sequence Diagram of CRP

## 3.2.4 Activity Diagram

The process flows in the system are captured in the activity diagram. Similar to a state diagram, an activity diagram also consists of activities, actions, transitions, initial and final states ,and guard conditions

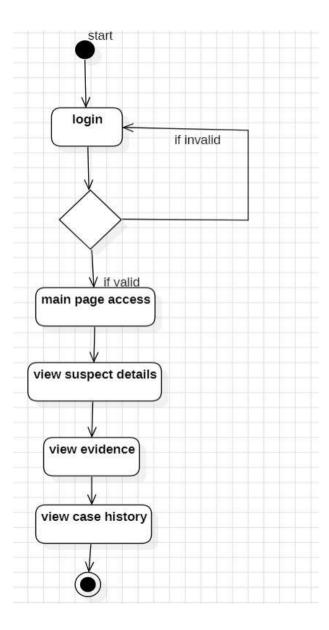


Fig 3.2.3 Activity Diagram of CRPAML

#### **IMPLEMENTATION**

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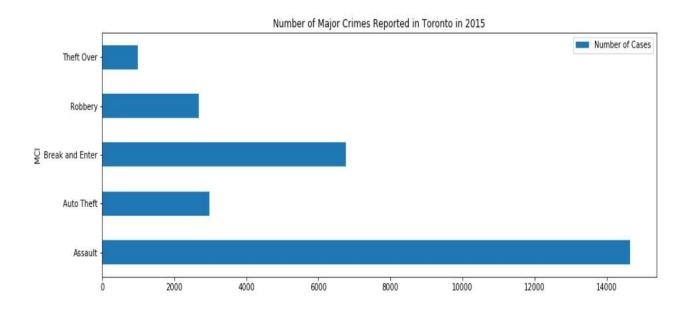
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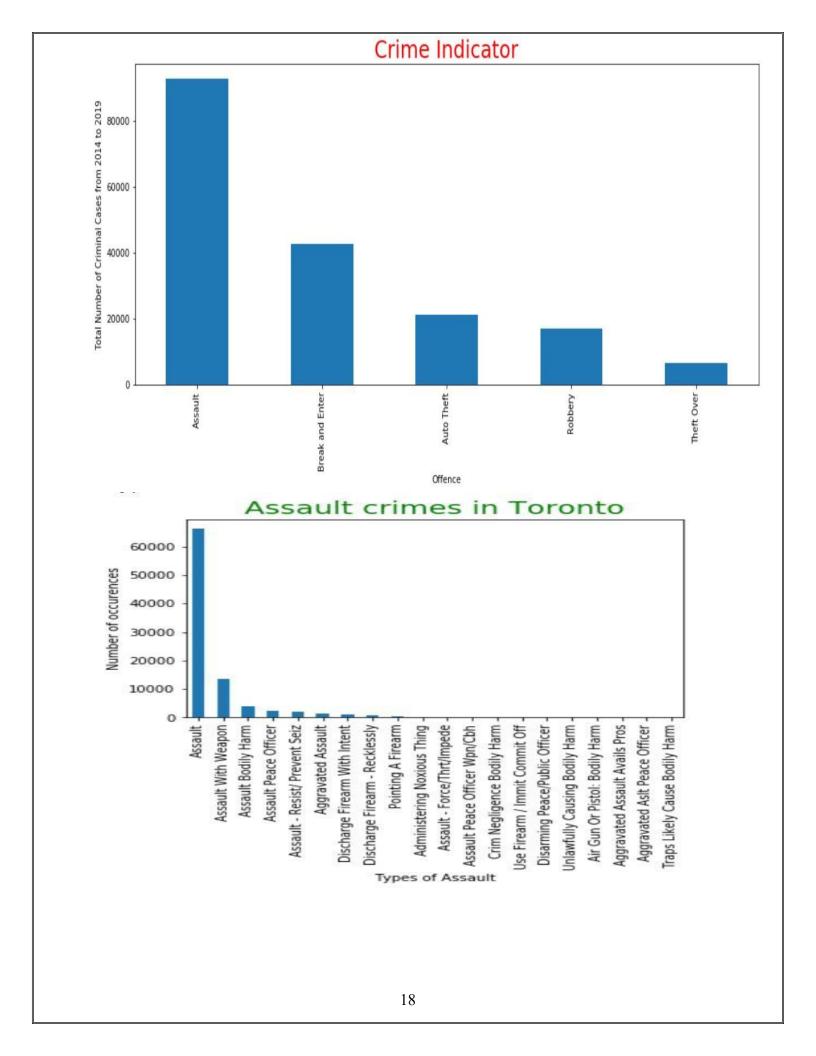
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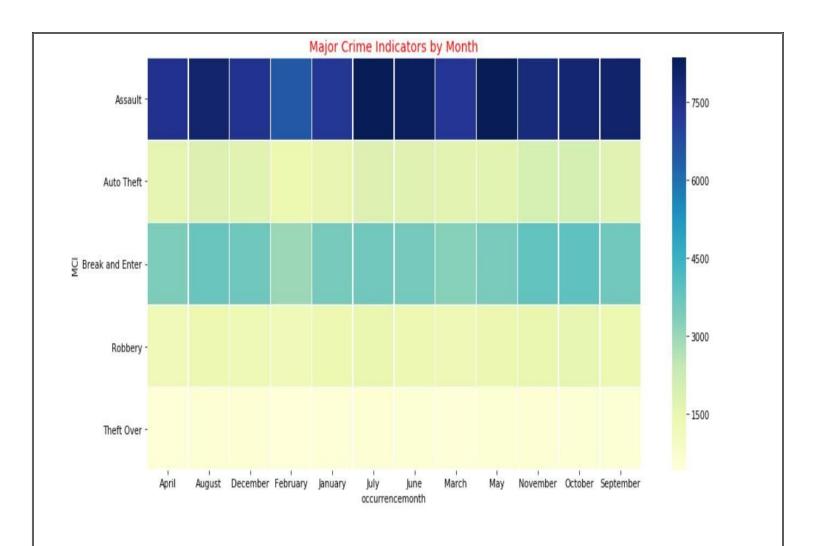
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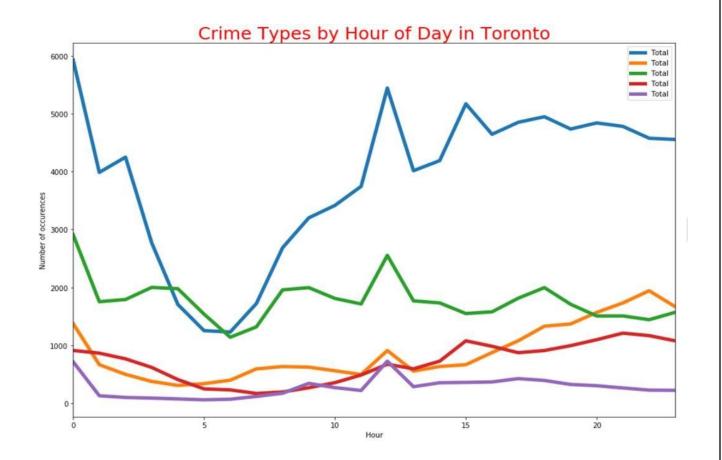
#### 4.2: Output Screens







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1	0	1	15.0	1	1	1	0	1	1	0	1
2	0	1	16.0	2	2	2	1	2	2	1	2
3	0	2	26.0	3	3	3	1	2	3	2	3
4	0	0	18.0	0	0	4	0	3	4	0	0



## **4.3: Testing**

Software testing is a critical element of software quality assurance and represents the ultimate review of specification, design and code generation.

#### **CONCLUSION & FUTURE SCOPE**

#### 5.1: Conclusion

Machine learning is used for predicting and analysing crime rates. By leveraging vast datasets and sophisticated algorithms, ML models can uncover hidden patterns and correlations within crime data, aiding law enforcement agencies and policymakers in making informed decisions. However, it's essential to acknowledge the limitations and challenges inherent in this approach. Factors such as data biases, privacy concerns, and the dynamic nature of criminal behavior can impact the accuracy and reliability of predictions. Additionally, while ML can provide valuable insights, it should be used in conjunction with human expertise and ethical considerations to ensure fair and responsible use. Despite these challenges, the ongoing advancements in machine learning techniques hold the potential to enhance crime prevention strategies and contribute to safer communication

#### **5.2: Future Scope**

The future scope for a project focused on crime rate prediction and analysis using machine learning is promising. By leveraging advanced algorithms and vast datasets, such a system could help law enforcement agencies and policymakers better understand crime patterns and trends. Machine learning models could analyse historical crime data to identify patterns, correlations, and predictive factors that contribute to criminal activities. Additionally, the system could incorporate real-time data streams from various sources such as social media, weather patterns, or economic indicators to enhance its predictive capabilities. Overall, the project holds potential to make significant contributions to crime prevention and public safety efforts

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