A

**Project Report**

On

# Road Accident Prediction and Classification

submitted as partial fulfillment for the award of`

# BACHELOR OF TECHNOLOGY DEGREE

SESSION 2024-25

In

## Computer Science and Engineering

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(Formerly UPTU)

**May,2025**

# DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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# CERTIFICATE

This is to certify that Project Report entitled "**Road Accident Prediction and Classification**" Project Group No.: 69 which is submitted by **Harshit Goel, Harsheet, and Mohit Saini** in partial fulfillment of the requirement for the award of degree B. Tech. in the Department of Computer Science & Engineering of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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# ACKNOWLEDGEMENT

It gives us a great sense of pleasure to present the report of the B. Tech Project undertaken during B. Tech. Final Year. We owe special debt of gratitude to Upendra Mishra, Department of Computer Science & Engineering, KIET, Ghaziabad, for his constant support and guidance throughout the course of our work. His sincerity, thoroughness and perseverance have been a constant source of inspiration for us. It is only his cognizant efforts that our endeavors have seen light of the day.

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# ABSTRACT


## Objective

This research develops a machine learning system to predict road accident severity, contributing to enhanced traffic safety measures. The system addresses the critical need for proactive accident prevention through intelligent forecasting capabilities.

## Methodology

We implemented a comprehensive machine learning approach using a dataset containing 1.6 million accident records from 2005-2015. The system employs classification algorithms including Decision Trees, Random Forest, and Logistic Regression to analyze multiple factors such as environmental conditions, road characteristics, and driver demographics.

## Key Findings

Our Random Forest model achieved 86.86% accuracy, significantly outperforming traditional prediction methods. The system successfully identifies high-risk scenarios and provides real-time severity predictions based on input parameters.

## Impact

The developed web application enables authorities to implement preventive measures proactively, potentially reducing accident rates and improving road safety management through data-driven insights.

# TABLE OF CONTENTS

# CHAPTER 1

# INTRODUCTION

## 1.1 Background

Road traffic accidents represent a significant global challenge, causing approximately 1.2 million fatalities annually according to World Health Organization statistics. This translates to roughly 3,300 deaths daily, with an additional 50 million individuals suffering injuries. The economic impact reaches approximately $43 billion in direct losses annually, highlighting the urgent need for effective prevention strategies.

Current accident prediction methodologies face several limitations:

- Traditional linear models inadequately capture the complex, non-linear nature of traffic systems
- Existing backpropagation neural networks suffer from convergence issues and reduced accuracy
- Limited real-time prediction capabilities for dynamic traffic scenarios

## 1.2 Problem Statement

The complexity of road accident causation involves multiple interconnected factors including driver behavior, environmental conditions, vehicle characteristics, and infrastructure elements. Traditional prediction approaches fail to adequately model these relationships, resulting in:

1. Insufficient accuracy in severity prediction
2. Inability to provide real-time risk assessment
3. Limited integration with preventive action systems
4. Poor scalability for large-scale deployment

## 1.3 Project Objectives

This project aims to:

1. Develop Advanced Prediction Models: Create machine learning algorithms capable of accurately predicting accident severity based on multiple input parameters

2. Build Real-time System: Implement a web-based application for immediate risk assessment
3. Enable Preventive Actions: Integrate alert mechanisms for traffic authorities to enable proactive interventions
4. Validate Performance: Demonstrate improved accuracy compared to existing methodologies

## 1.4 Scope and Applications

The system's applications include:

- Traffic management optimization
- Emergency response planning
- Infrastructure improvement prioritization
- Public safety policy development
- Insurance risk assessment

# CHAPTER 2
# LITERATURE REVIEW

A comprehensive literature survey forms the foundation of any software development project, providing insights into existing research, methodologies, and technological advancements in the field. This review examines current approaches to traffic accident prediction and identifies opportunities for improvement through machine learning applications.

## Table 1: Literature Review

| S. No. | Title | Author | Year | Objectives |
|---|---|---|---|---|
| 1 | Road Accident Prediction and Classification using Machine learning | Devansh Pradhan, Apurv Upadhyay, Ashish Gupta, Arpita Pandey, Dr. Rajkumar Gaur | 2023 | The objective of this research is to develop a machine learning-powered web application capable of predicting the severity of road accidents based on real-time input conditions such as vehicle type, weather, road surface, and driver demographics. |
| 2 | Road Accident Analysis and Prediction using Machine Learning Algorithmic Approaches | Koteswara Rao Ballamudi | 2019 | Traditional way of linear analyses can not reveal the really situation the result of prediction is not satisfactory. Compares traditional BP network with its proposed solution. |

| | | | | |
|---|---|---|---|---|
| 3 | Evolutionary Cross Validation | Thineswaran Gunasegaran Yu-N Cheah | 2017 | This paper proposes an evolutionary cross validation algorithm for identifying optimal folds in a dataset to improve predictive modeling accuracy |
| 4 | On the Selection of Decision Trees in Random Forests | Simon Bernard, Laurent Heutte and Sebastien Adam | 2017 | This paper presents a study on on the Random Forest (RF) family of ensemble methods. |
| 5 | Hyper-parameter Tuning of a Decision Tree Induction Algorithm | Rafael G.Mantovan,, Ricardo Cerri,Joaquin Vanschoren | 2016 | This paper investigates how sensitive decision trees are to a hyper-parameter optimization process. Four different tuning techniques were explored.. |

2 The analysis of global traffic safety statistics reveals alarming trends in accident frequency and severity. Current research indicates that traditional linear analysis methods inadequately capture the complex relationships inherent in traffic accident scenarios. The multifaceted nature of accident causation requires sophisticated modeling approaches that can handle non-linear relationships and diverse data types.

3 Recent developments in machine learning have opened new possibilities for accident prediction. Deep learning methodologies demonstrate particular promise in modeling complex traffic scenarios, though implementation challenges remain significant. The integration of multiple data sources including weather conditions, traffic patterns, and infrastructure characteristics has shown potential for improving prediction accuracy.

## 2.1 Prediction Factors and Data Sources

Traffic accident prediction systems rely on comprehensive datasets that capture various contributing factors. The primary data source for this research comes from government repositories, specifically the UK traffic data portal. This dataset encompasses comprehensive accident records collected through standardized reporting mechanisms over an extended period from 2005 to 2015.

The dataset structure includes multiple categories of information, each represented in numerical format for computational efficiency. Supporting documentation provides detailed

explanations for each categorical variable, ensuring proper interpretation and analysis.

**Table 1.** *Prediction Factors.*

| |
|---|
| **Day_of_Week** :Numeric: 1 for Sunday, 2 for Monday, and so on. |
| **Latitude and Longitude** |
| **Light_Conditions :** Day, night, street lights or not. |
| **Weather_Conditions:** Wind, rain, snow, fog. |
| **Vehicle Type:** Pedal cycle, Motorcycle, Car |
| **Road_Surface_Conditions** :Wet, snow, ice, flood. |

| |
|---|
| **Speed Limit :** 60 mph , 70 mph |
| **Output** |
| **Accident Severity** : 1 = Fatal, 2 = Serious, 3 = Slight |

# CATEGORY AND MEANING OF WEATHER AND LIGHT CLASSIFICATION FACTORS

**Table 3.** *Weather Conditions*

| code | label |
|---|---|
| 1 | Fine no high winds |
| 2 | Raining no high winds |
| 3 | Snowing no high winds |
| 4 | Fine + high winds |
| 5 | Raining + high winds |
| 6 | Snowing + high winds |
| 7 | Fog or mist |
| 8 | Other |
| 9 | Unknown |
| -1 | Data missing or out of range |

**Table 4.** *Light Conditions*

| code | label |
|---|---|
| 1 | Daylight |
| 4 | Darkness - lights lit |
| 5 | Darkness - lights unlit |
| 6 | Darkness - no lighting |
| 7 | Darkness - lighting unknown |
| -1 | Data missing or out of range |

Road Surface Conditions and Gender of Driver and Vehicle Type

**Table 5.** *Road Conditions*

| code | label |
|---|---|
| 1 | Dry |
| 2 | Wet or damp |
| 3 | Snow |
| 4 | Frost or ice |
| 5 | Flood over 3cm. deep |
| 6 | Oil or diesel |
| 7 | Mud |
| -1 | Data missing or out of range |

**Table 6.** *Gender*

| code | label |
|---|---|
| 1 | Male |
| 2 | Female |
| 3 | Not known |
| -1 | Data missing |

**Table 7.** *Vehicle Type*

| code | label |
|---|---|
| 1 | Pedal cycle |
| 2 | Motorcycle 50cc and under |
| 3 | Motorcycle 125cc and under |
| 4 | Motorcycle over 125cc and up to 500cc |
| 5 | Motorcycle over 500cc |
| 8 | Taxi/Private hire car |
| 9 | Car |
| 10 | Minibus (8 - 16 passenger seats) |
| 11 | Bus or coach (17 or more pass seats) |
| 16 | Ridden horse |
| 17 | Agricultural vehicle |
| 18 | Tram |
| 19 | Van / Goods 3.5 tonnes mgw or under |
| 20 | Goods over 3.5t. and under 7.5t |
| 21 | Goods 7.5 tonnes mgw and over |
| 22 | Mobility scooter |
| 23 | Electric motorcycle |
| 90 | Other vehicle |
| 97 | Motorcycle - unknown cc |
| 98 | Goods vehicle - unknown weight |
| -1 | Data missing or out of range |

**Table 8.** *Day of The Week*

| code | label |
|---|---|
| 1 | Sunday |
| 2 | Monday |
| 3 | Tuesday |
| 4 | Wednesday |
| 5 | Thursday |
| 6 | Friday |
| 7 | Saturday |

## 2.2 Model Validation Approaches

Machine learning applications in supervised learning scenarios require robust training methodologies to ensure reliable performance. The development of accurate classification and regression models depends heavily on the availability of comprehensive labeled datasets that include both input features and target variables.

Effective model training requires substantial amounts of quality data to capture underlying patterns and relationships. The validation process involves testing trained models with independent datasets to evaluate predictive accuracy and generalization capability.

Traditional approaches often employ simple train-test splits, typically using ratios such as 80:20 or 60:40. However, this single-split methodology can introduce bias due to uneven data distribution, where certain data clusters may be concentrated in either training or testing subsets.

Cross-validation methodologies address these limitations by employing multiple unique train-test combinations, known as folds. This approach ensures that all data points have opportunities to serve as both training and testing data across different iterations, reducing bias and improving model reliability.

## 2.3 Decision Tree and Ensemble Methods

Decision tree algorithms provide intuitive, flowchart-like structures for classification tasks. Each internal node represents a decision point based on attribute values, branches represent possible outcomes, and leaf nodes contain final classification results. The hierarchical structure resembles human decision-making processes, making these models

highly interpretable.

Decision tree components include:

- **Decision Nodes**: Represented by squares, indicating decision points
- **Chance Nodes**: Circular representations for probabilistic outcomes
- **Terminal Nodes**: Triangular endpoints containing final classifications

Machine learning ensemble methods combine multiple individual classifiers to create more robust prediction systems. This approach leverages the complementary strengths of different models to improve overall performance. Ensemble techniques such as Boosting, Bagging, and Random Forests have demonstrated superior performance compared to single-model approaches.

The effectiveness of ensemble methods depends on achieving optimal diversity among component classifiers. This diversity enables the ensemble to make correct predictions through consensus while minimizing the impact of individual model errors.

Random Forest algorithms represent a particularly successful ensemble approach, combining multiple randomized decision trees. However, traditional Random Forest implementations face challenges including the need to predetermine the number of trees and reduced interpretability due to randomization processes.

## 2.4 Hyperparameter Optimization

Decision tree algorithms include numerous hyperparameters that significantly influence model performance. The optimization of these parameters requires systematic approaches due to the vast number of possible combinations. Recent research has focused on developing efficient optimization techniques to identify optimal parameter configurations.

Supervised classification represents one of the most extensively studied areas in machine learning. Decision tree algorithms maintain popularity due to their robustness, computational efficiency, and ability to produce interpretable models. These algorithms demonstrate particular strength in handling diverse data types while maintaining satisfactory accuracy levels across multiple application domains.

The performance of machine learning algorithms depends critically on hyperparameter selection. Poor parameter choices can significantly degrade model performance, while

optimal configurations can substantially improve accuracy. This relationship has motivated extensive research into automated optimization techniques.

Contemporary optimization approaches include:

- **Grid Search**: Systematic exploration of predefined parameter ranges
- **Random Search**: Probabilistic sampling of parameter space
- **Bayesian Optimization**: Model-based optimization using prior knowledge
- **Evolutionary Algorithms**: Population-based optimization inspired by natural selection

The application of these optimization techniques to decision tree algorithms has demonstrated consistent improvements in predictive performance, though the magnitude of improvement varies across different datasets and problem domains.

# CHAPTER 3

# PROPOSED METHODOLOGY

The development of our road accident prediction system follows a comprehensive approach integrating

multiple components for effective real-time prediction and response. Our solution consists of four primary modules working in coordination to deliver accurate predictions and timely alerts.

## System Overview:

The **Virtual Machine** serves as the central processing unit, hosting the trained machine learning algorithms along with frontend and backend servers deployed for optimal performance.

The **Frontend (User Interface)** utilizes Geolocation API to automatically capture user location, which is then processed through OpenWeatherMap API to retrieve current geographical and weather conditions. Users can input additional parameters including age, gender, and vehicle specifications. The interface also provides access to national accident heatmap visualizations.

The **Backend (Administration)** manages server operations and maintenance, processes user inputs through the machine learning model, and generates severity predictions. The system can transmit severity assessments and location data to law enforcement for preventive action implementation.

The **Machine Learning Algorithm** implements multiple classification techniques including Decision Trees, Random Forest, and Logistic Regression with hyperparameter optimization for maximum accuracy. Random Forest demonstrated superior performance with 86% accuracy and was selected as the primary model for the web application.

## 3.1 System Architecture

The system architecture follows a modular design approach ensuring scalability and maintainability. The data flow representation illustrates the interaction between different system components.

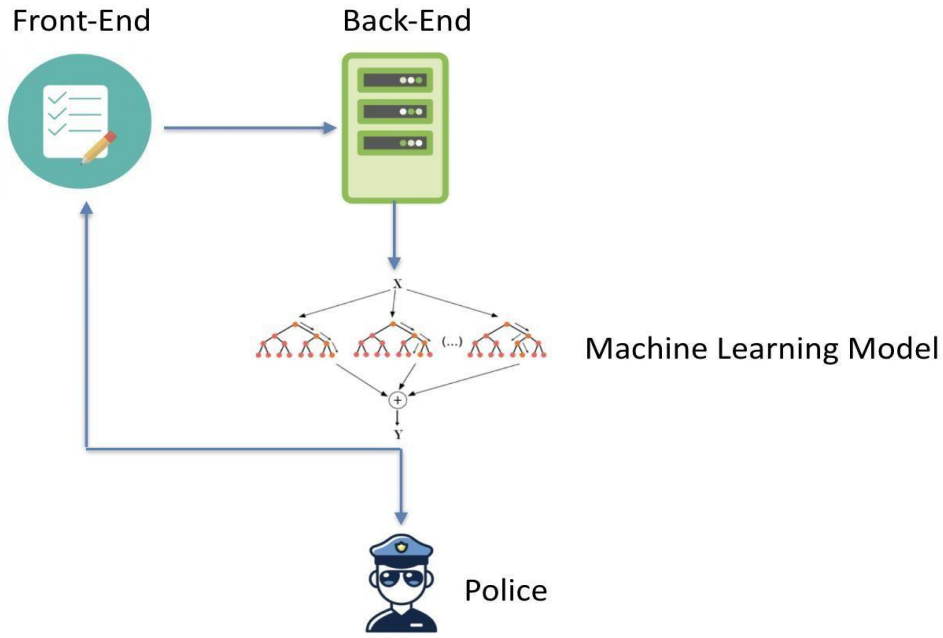



**Figure 3.1** System mode

## 3.2 Modules

### 3.2.1 Virtual Machine Infrastructure

The core computational infrastructure hosts all system components including trained machine learning models and web services. This centralized approach ensures consistent performance and simplified maintenance procedures.

**3.2.2 Frontend User Interface**

The user-facing component provides intuitive interaction capabilities:

- **Automatic Location Detection:** Geolocation API integration for precise coordinate capture
- **Weather Data Integration:** Real-time weather condition retrieval through OpenWeatherMap API
- **Manual Input Collection:** User-provided demographic and vehicle information
- **Visualization Dashboard**: Interactive accident heatmap display for national overview

### 3.2.2 Backend Administrative System

Server-side operations manage the complete prediction workflow:

- **Server Management:** Maintains system stability and performance
- **Data Processing:** Feeds collected inputs into machine learning models
- **Prediction Generation:** Processes severity assessments using trained algorithms
- **Communication System:** Transmits alerts to relevant authorities for preventive measures

### 3.2.3 Machine Learning Processing

The core analytical component implements advanced classification algorithms:

- **Algorithm Implementation:** Decision Trees, Random Forest, and Logistic Regression
- **Optimization Techniques:** Hyperparameter tuning for enhanced accuracy
- **Model Selection:** Random Forest chosen based on superior 86% accuracy performance
- **Prediction Output:** Severity classification (Fatal, Serious, Slight)

## 3.3 Technology Stack

### 3.3.1 Python Programming Environment

Python serves as the primary development language due to its versatility and extensive library ecosystem. As a high-level, interpreted programming language, Python provides excellent readability and allows developers to express complex concepts efficiently.

Key Python characteristics supporting this project:

- **Interpreted Nature**: Enables rapid development and testing cycles
- **Dynamic Type System**: Flexible data handling capabilities
- **Comprehensive Libraries**: Extensive ecosystem for data science and web development
- **Cross-platform Compatibility**: Deployment flexibility across different operating systems
- **Object-Oriented Support**: Structured code organization and maintainability

Python's popularity in data science and machine learning makes it an ideal choice for this application, with widespread adoption by major technology companies and research institutions.

### 3.3.2 NumPy - Numerical Computing Foundation

NumPy provides the fundamental numerical computing capabilities

required for scientific analysis and machine learning operations.

Core NumPy features utilized:

- **N-dimensional Arrays**: Efficient storage and manipulation of large datasets
- **Mathematical Functions**: Comprehensive mathematical operations for data processing
- **Broadcasting Capabilities**: Advanced array operations for complex computations
- **Integration Support**: Seamless connectivity with other scientific libraries
- **Performance Optimization**: C-based implementation for high-speed computations

The library's array-based approach enables efficient processing of accident

data, supporting both matrix operations and element-wise computations essential for machine learning algorithms.

### 3.3.3 Google Collaboratory Development Environment

Google Colaboratory provides a cloud-based Jupyter notebook environment for model development and training, offering several advantages for this project:

- **Free Access**: No-cost access to computational resources including GPU support
- **Collaboration Features**: Team-based development capabilities
- **Pre-installed Libraries**: Comprehensive machine learning and data science libraries
- **Cloud Storage Integration**: Seamless Google Drive connectivity for data management
- **Jupyter Compatibility**: Standard notebook interface for interactive development

The Colaboratory environment proved essential for handling large-scale model training tasks and collaborative development among team members.

### 3.3.4 Scikit-learn Machine Learning Library

Scikit-learn provides the core machine learning algorithms and utilities used throughout this project:

**Key Features:**

- **Classification Algorithms**: Implementation of Decision Trees, Random Forest, and Logistic Regression
- **Model Selection Tools**: Cross-validation and hyperparameter optimization utilities
- **Preprocessing Functions**: Data scaling, encoding, and transformation capabilities
- **Evaluation Metrics**: Comprehensive performance assessment tools
- **Pipeline Support**: Streamlined workflow management for complex processing chains

The library's consistent API design and extensive documentation facilitated rapid development and experimentation with different modeling approaches.

### 3.3.5 Microsoft Azure Cloud Platform

Microsoft Azure provides the cloud infrastructure supporting the deployed application:

**Infrastructure Services:**

- **Virtual Machine Hosting**: Scalable compute resources for application deployment
- **Storage Solutions**: Reliable data storage and backup capabilities
- **Networking Services**: Load balancing and traffic management
- **Security Features**: SSL certificate management and access control
- **Monitoring Tools**: Performance tracking and system health monitoring

**Service Categories:**

1. **Infrastructure as a Service (IaaS)**: Virtual machine provisioning and management
2. **Platform as a Service (PaaS)**: Application hosting and deployment services
3. **Software as a Service (SaaS)**: Integrated software solutions and APIs

The Azure platform provides over 600 different services, offering comprehensive support for modern application development and deployment.

### 3.3.6 Domain Management and Security

**Custom Domain Implementation:** Professional domain registration and management provide user-friendly access to the application. The custom domain enhances credibility and provides memorable access points for end users.

**SSL Certificate Integration:** Security implementation through SSL certificates ensures encrypted communication between users and the application. HTTPS protocol implementation provides:

- **Data Encryption**: Secure transmission of sensitive location and personal information

- **Authentication**: Verification of server identity to prevent man-in-the-middle attacks
- **Integrity**: Protection against data tampering during transmission
- **Compliance**: Meeting security standards for web applications handling personal data

## 3.4 Application Programming Interfaces (APIs)

### 3.4.1 Geolocation API

The Geolocation API provides accurate location detection capabilities using multiple positioning methods:

**Technical Implementation:**

- **Cell Tower Triangulation**: Position estimation based on cellular network signals
- **WiFi Positioning**: Location determination using nearby wireless networks
- **GPS Integration**: Satellite-based positioning for enhanced accuracy
- **HTTPS Communication**: Secure data transmission using POST requests
- **JSON Data Format**: Standardized request and response formatting

The API returns location coordinates with accuracy radius information, enabling precise accident location identification for prediction purposes.

### 3.4.2 OpenWeatherMap API

Weather data integration provides real-time environmental conditions essential for accident prediction:

**Available Data Types:**

- **Current Weather**: Real-time temperature, humidity, and precipitation data
- **Weather Forecasts**: Short-term and extended weather predictions
- **Historical Data**: Past weather patterns for trend analysis
- **Specialized Indices**: UV index, air quality, and visibility measurements
- **Severe Weather Alerts**: Warnings for hazardous weather conditions

The comprehensive weather data enables the system to assess environmental risk factors that significantly influence accident probability and severity.

### 3.4.3 SMS Notification API

TextLocal API integration provides reliable message delivery for emergency notifications:

**Service Features:**

- **Instant Delivery**: Rapid message transmission to designated recipients

- **Delivery Confirmation**: Status tracking for successful message delivery
- **Bulk Messaging**: Support for multiple recipient notifications
- **Message Customization**: Personalized content based on prediction results
- **Integration Simplicity**: Easy implementation with minimal development overhead

The SMS system ensures that relevant authorities receive immediate notifications when high-severity accident predictions are generated.

## 3.5 Secure Shell (SSH) Client Implementation

SSH provides secure remote access to the deployed application infrastructure:

**Security Features:**

- **Encrypted Communication**: Cryptographic protection for all data transmission
- **Authentication Methods**: Multiple verification approaches including key-based authentication
- **Network Security**: Protection against eavesdropping and connection hijacking
- **Cross-Platform Support**: Compatibility with various operating systems
- **Remote Administration**: Secure server management and maintenance capabilities

SSH replaced insecure protocols like Telnet, providing essential security for production system management. The implementation uses standard port 22 and OpenSSH for maximum compatibility.

## 3.6 Diagrammatic Representation

### 3.6.1 Data flow diagram

**3.6.1.1** A data flow diagram (DFD) maps out the flow of information for any process or system. It uses defined symbols like rectangles, circles and arrows, plus short text labels, to show data inputs, outputs, storage points and the routes between each destination. Data flowcharts can range from simple, even hand-drawn process overviews, to in-depth, multi-level DFDs that dig progressively deeper into how the data is handled. They can be used to analyze an existing system or model a new one. Like all the best diagrams and charts, a DFD can often visually "say" things that would be hard to explain in words, and they work for both technical and nontechnical audiences, from developer to CEO. That's why DFDs remain so popular after all these years. While they work well for data flow software and systems, they are less applicable nowadays to visualizing interactive, real-time database-oriented software or systems.

#### 3.6.1.2 DFD level 0

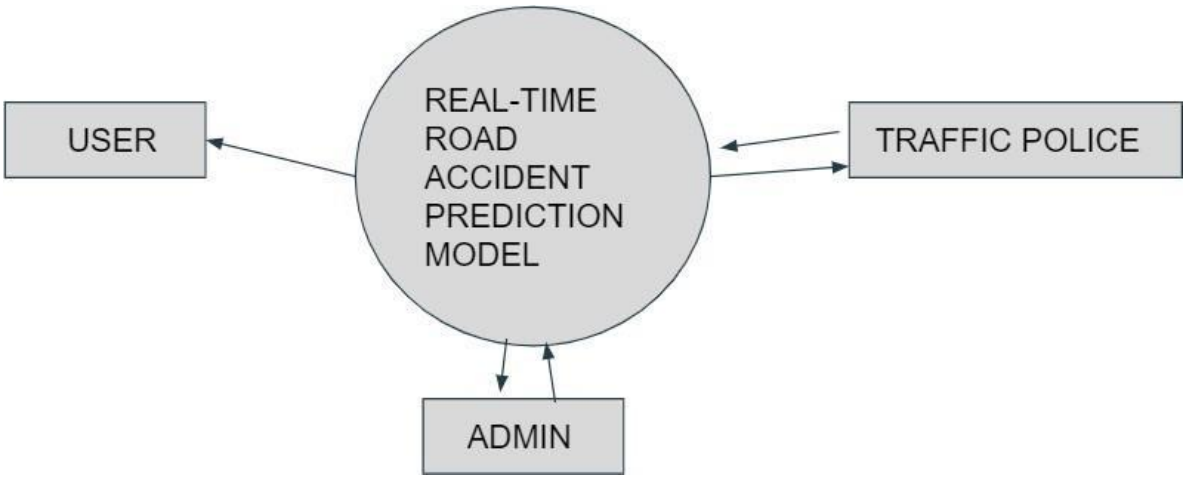



**Figure 4.1.1** DFD level 0

- Admin : is responsible for building the ML model and maintaining it.
- User : the person who views the output.
- Traffic police : they take respective action according to the output predicted by the ML model.

### 3.6.1.3 DFD level 1

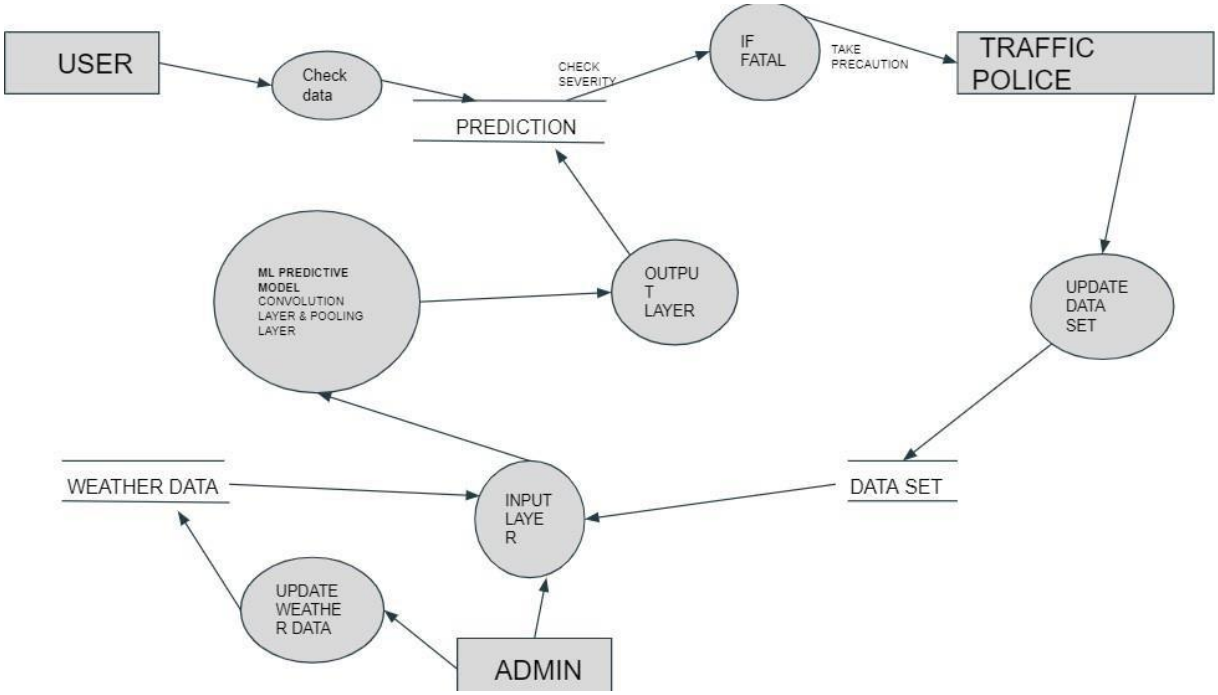



**Figure 4.1.2** DFD level 1

3.6.1.3.1 The ML model is further divided into 3 layer

- Input layer
- Convolution layer or Pooling layer
- Output layer

3.6.1.3.2 If the output predicted is severity FATAL , which means that there is high probability for an accident to occur, so an alert is send to the traffic police to take respective action.

### 3.6.2 UML Modeling and System Analysis

UML is the international standard notation for object-oriented analysis and design. The object management group defines it. The heart of object-oriented problem solving is the construction of a model. The model abstracts the essential details of the underlying problem from its usually complicated real world. The scope UML is a language for specifying artifacts, visualizing artifacts, constructing artifacts and documenting artifacts. UML provides the following diagrams to represent the software process:

- Class Diagram
- Use Case diagram
- Sequence diagram

#### 3.6.2.1 Class Diagram

Class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among objects.

The class diagram is the main building block of object-oriented modeling. It is used for general conceptual modeling of the structure of the application, and for detailed modeling translating the models into programming code. Class diagrams can also be used for data modeling. The classes in a class diagram represent both the main elements, interactions in the application, and the classes to be programmed.

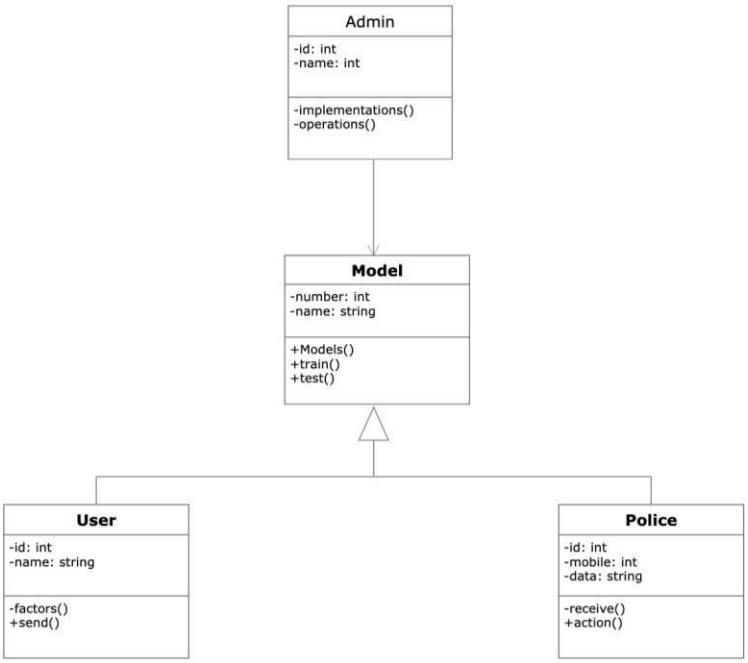



**Figure 4.2.3** Class diagram

## 3.6.2.2Use Case Diagram

A use case diagram at its simplest is a representation of a user's interaction with the system that shows the relationship between the user and the different use cases in which the user is involved. A use case diagram can identify the different types of users of a system and the different use cases and will often be accompanied by other types of diagrams as well. The use cases are represented by either circles or ellipses.

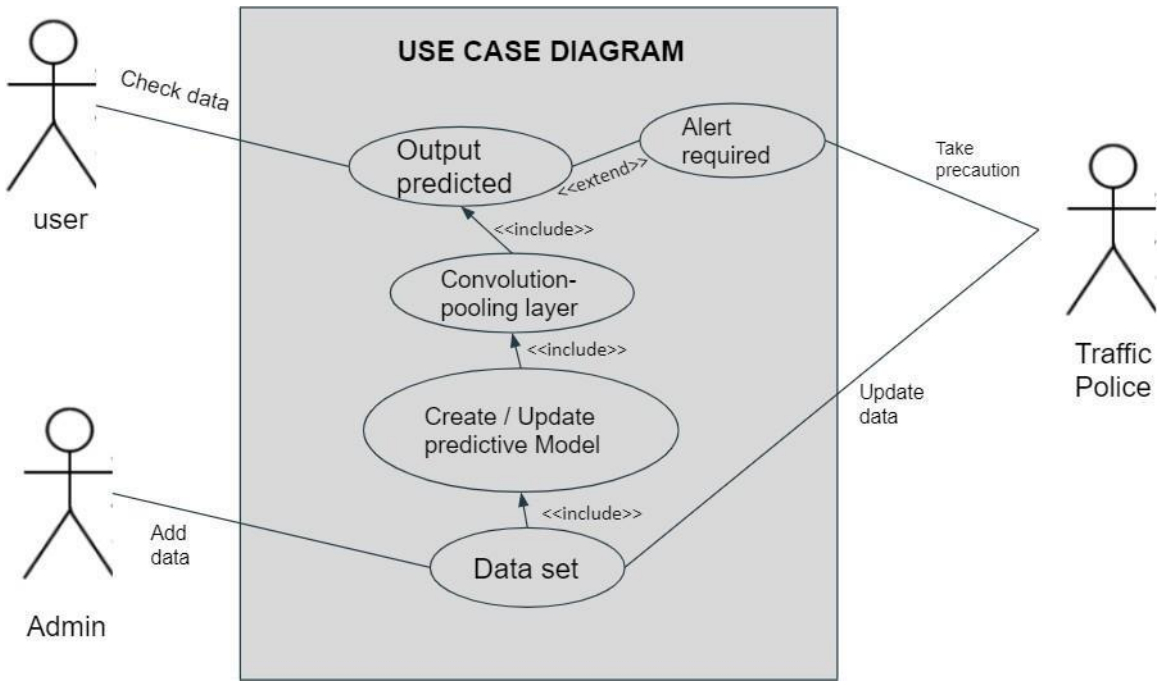



**Figure 4.2.2** Usecase diagram

3.6.2.2.1 In the system, there are two actors:user and play store.

3.6.2.2.2 The user performs the tasks of searching for an application and viewing the result if an application is malicious.

3.6.2.2.3 The play store downloads the required application and its comments.

3.6.2.2.4 The other actions performed in the system are testing and sentiment analysis on the download application and comments.

### 3.6.2.3 Sequence Diagram

A sequence diagram shows object interactions arranged in time sequence. It depicts the objects and classes involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are typically associated with use case realizations in the Logical View of the system under development. Sequence diagrams are sometimes called event diagrams or event scenarios.

A sequence diagram shows, as parallel vertical lines (*lifelines*), different processes or objects that live simultaneously, and, as horizontal arrows, the messages exchanged between them, in the order in which they occur. This allows the specification of simple runtime scenarios in a graphical manner.

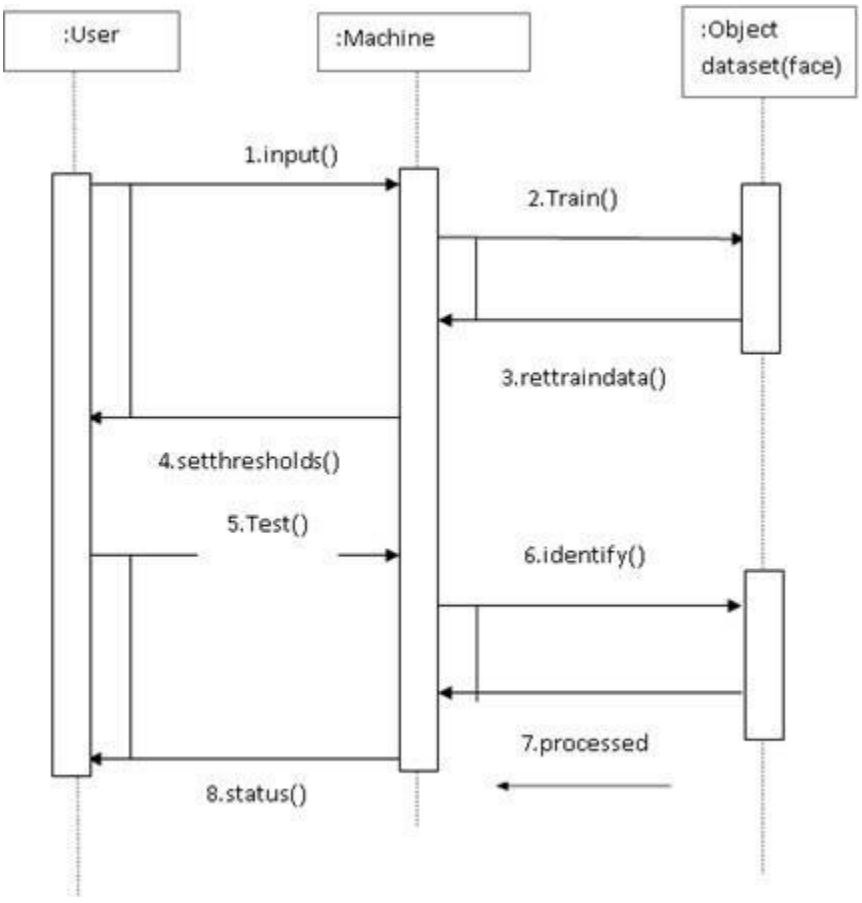


**Fig.** Sequence diagram

## 3.7 Implementation of Proposed solution

There are four important steps:

1. Preprocessing
2. Training
3. Testing
4. Web App Integration

### 3.7.1 Data Importing

We import three files to perform analysis on this data. This data is consist of three files that are accidents, casualties and vehicles. However, we have one more file which is general information about the traffic count for year 2000 to 2015. We can use general traffic information data for machine learning part.

- Importing of packages needed is done.
- 3 CSV files Accidents.csv Casualties.csv Vehicles.csv
- Using pandas to import data into dataframe
- accident.head() views top 5 rows of dataframe

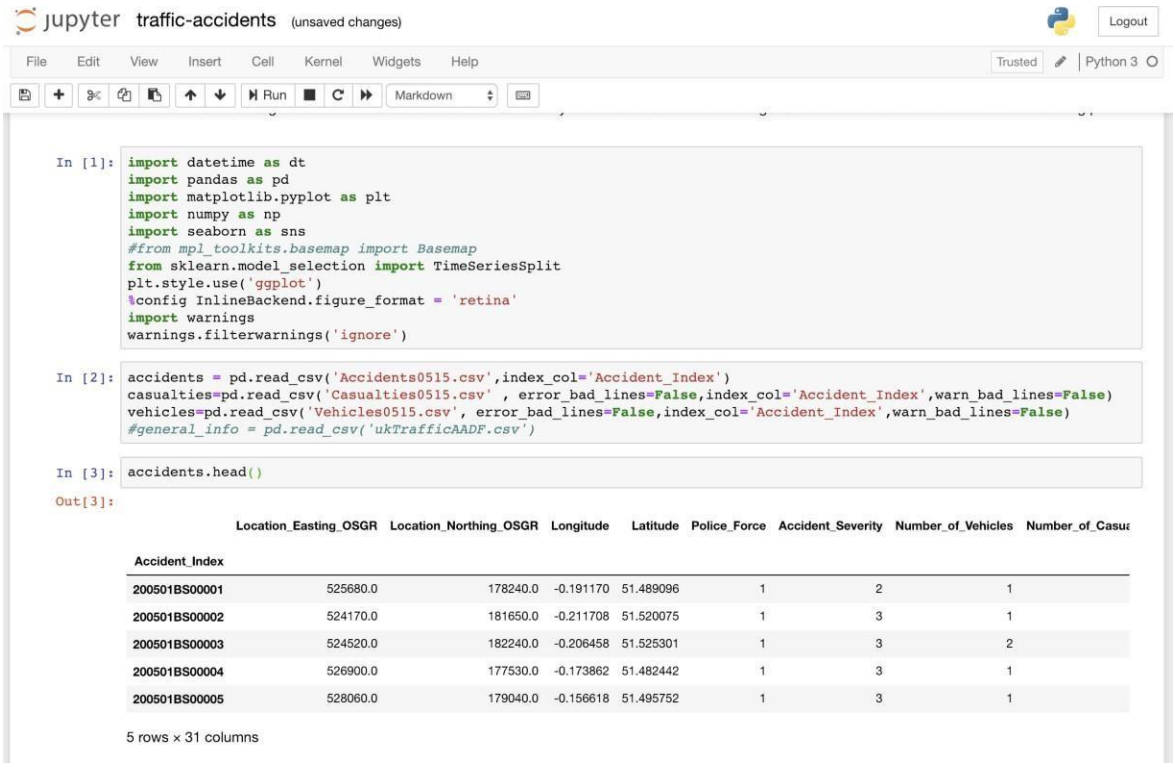



Fig 3.1 Importing

### 3.7.2Preprocessing of Data

## 3.7.2.1 Data Cleaning

Her we identify noisy, irrelevant data. We also understand through visualization which factors are more important.

## 3.7.2.2Identifying Missing Values

In this particular dataset, there are two types of missing values '-1' and 'Nan'. We will invesitigate each column with total missing values. We will not be imputing any mean or median value since the dataset is big enough to perform analysis.

```
In [5]: accidents.drop(['Location_Easting_OSGR', 'Location_Northing_OSGR','LSOA_of_Accident_Location',
                        'Junction_Control' ,'2nd_Road_Class'], axis=1, inplace=True)
        accidents['Date_time'] =  accidents['Date'] +' '+ accidents['Time']

        for col in accidents.columns:
            accidents = (accidents[accidents[col]!=-1])
            #print(col ,' ' , x)
        for col in casualties.columns:
            casualties = (casualties[casualties[col]!=-1])

            accidents['Date_time'] = pd.to_datetime(accidents.Date_time)
        accidents.drop(['Date','Time'],axis =1 , inplace=True)
        accidents.dropna(inplace=True)
```

Using join method to combine accidents and vehicles files as they have the same primary key Accident_Index.

```
In [4]: accidents = accidents.join(vehicles, how='outer')
```

**Fig 3.2** Join

## 3.8 Data Visualization

The first thing we can do is to find out about accidents time to get intution and some driver's age who are involved in the accident.

- We can find out the number of accidents on the days of a week.
- We can find out about the accidents number using hours of the day.
- Finding out about the age of driver can tell us more about the accidents.

## 3.8.1Accidents on Day Of Week

We can find out the number of accidents on the days of a week. As we can see that thursday has the highest amount of accidents in this dataset from 2005 to 2015. We have to keep in mind that accidents numbers could be depending on traffic amount on particular day.

```
In [6]: plt.figure(figsize=(12,6))
        accidents.Date_time.dt.dayofweek.hist(bins=7,rwidth=0.55,alpha=0.5, color= 'orange')
        plt.title('Accidents on the day of a week' , fontsize= 30)
        plt.grid(False)
        plt.ylabel('Accident count' , fontsize = 20)
        plt.xlabel('0 - Sunday ,  1 - Monday  ,2 - Tuesday , 3 - Wednesday , 4 - Thursday , 5 - Friday , 6 - Saturday' , fontsi

Out[6]: Text(0.5,0,'0 - Sunday ,  1 - Monday  ,2 - Tuesday , 3 - Wednesday , 4 - Thursday , 5 - Friday , 6 - Saturday')
```

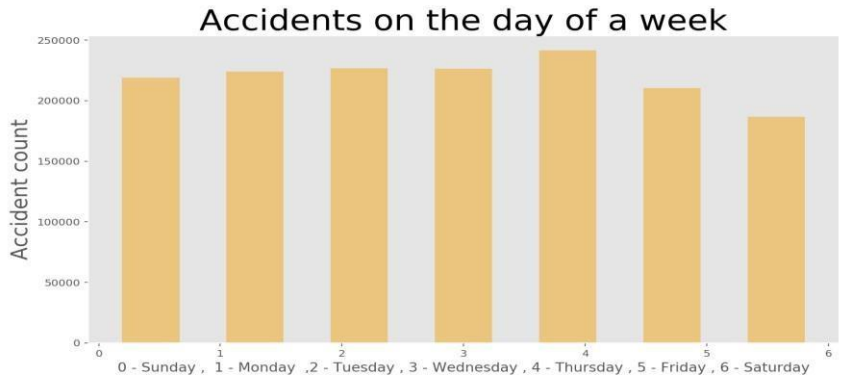



Fig 3.3 Accidents

### 3.8.2 Time of Accident

He we found out that the most of accidents happened around after noon. We can assume that this time of the day has the most traffic moving such as people leaving from work.

```
In [7]: plt.figure(figsize=(12,6))
        accidents.Date_time.dt.hour.hist(rwidth=0.75,alpha =0.50, color= 'orange')
        plt.title('Time of the day/night',fontsize= 30)
        plt.grid(False)
        plt.xlabel('Time 0-23 hours' , fontsize = 20)
        plt.ylabel('Accident count' , fontsize = 15)

Out[7]: Text(0,0.5,'Accident count')
```

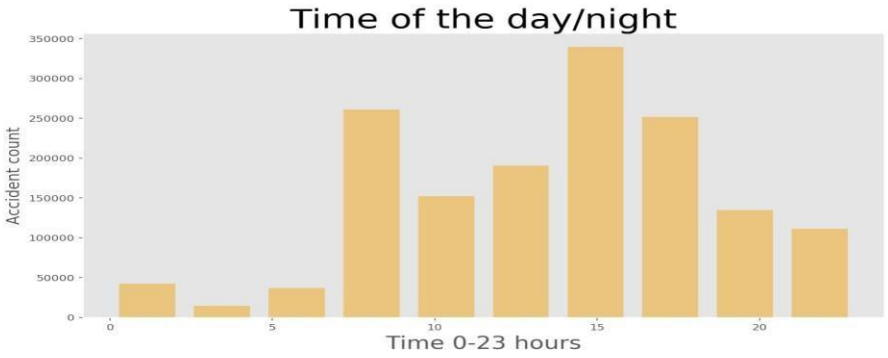



Fig 3.4 Time

### 3.8.3 Age Band of Casualties

In this dataset, age band is grouped in 11 different codes. We will create the labels and pass it to the plot as xticks so we can have idea about the bins representation

```
In [8]: objects = ['0','0-5','6-10','11-15','16-20','21-25','26-35',
                   '36-45', '46-55','56-65','66-75','75+']

        plt.figure(figsize=(12,6))
        casualties.Age_Band_of_Casualty.hist(bins = 11,alpha=0.5,rwidth=0.90, color= 'red',)
        plt.title('Age of people involved in the accidents', fontsize = 25)
        plt.grid(False)
        y_pos = np.arange(len(objects))
        plt.xticks(y_pos , objects)
        plt.ylabel('Accident count' , fontsize = 15)
        plt.xlabel('Age of Drivers', fontsize = 15,)

Out[8]: Text(0.5,0,'Age of Drivers')
```

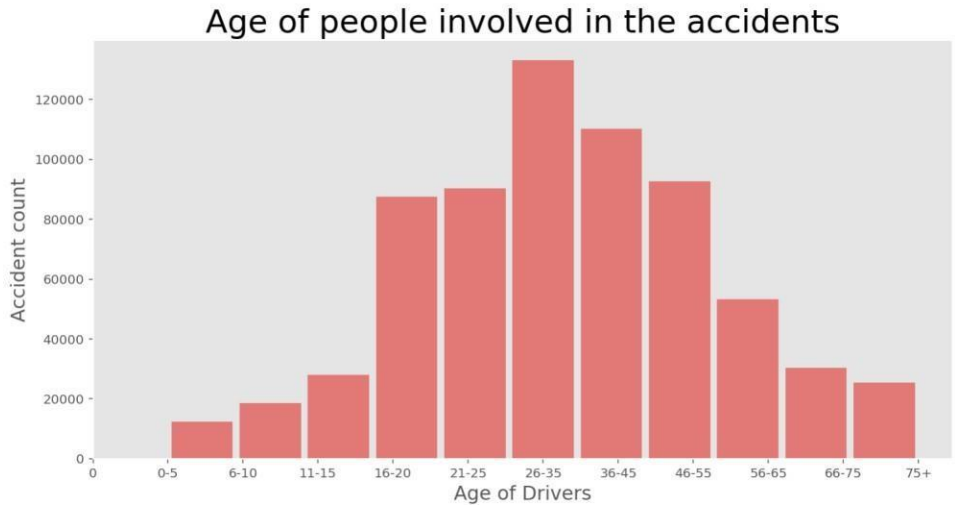



Fig 3.5 Age

This is very interesting fact about this dataset. Most of the drivers age is around 225 to 35 who are involved in the accident. However, we do not know the number of drivers with age 25 to 35 on the road compare to other ages. Intuitively, I would assume that the driver with age 25 to 35 are more in the number of drivers with different age.

### 3.8.4 Co-relation between variables

Since our dataset is in numeric values. We can find out correlation between columns.

As we see that there is not so much strong correlations between any variables. There is only one positive strong correlation between speed limit and Urban or Rural Area.

```
In [52]: corr =  accidents.corr()
         plt.subplots(figsize=(20,9))
         sns.heatmap(corr)

Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x1a3fde1c50>
```

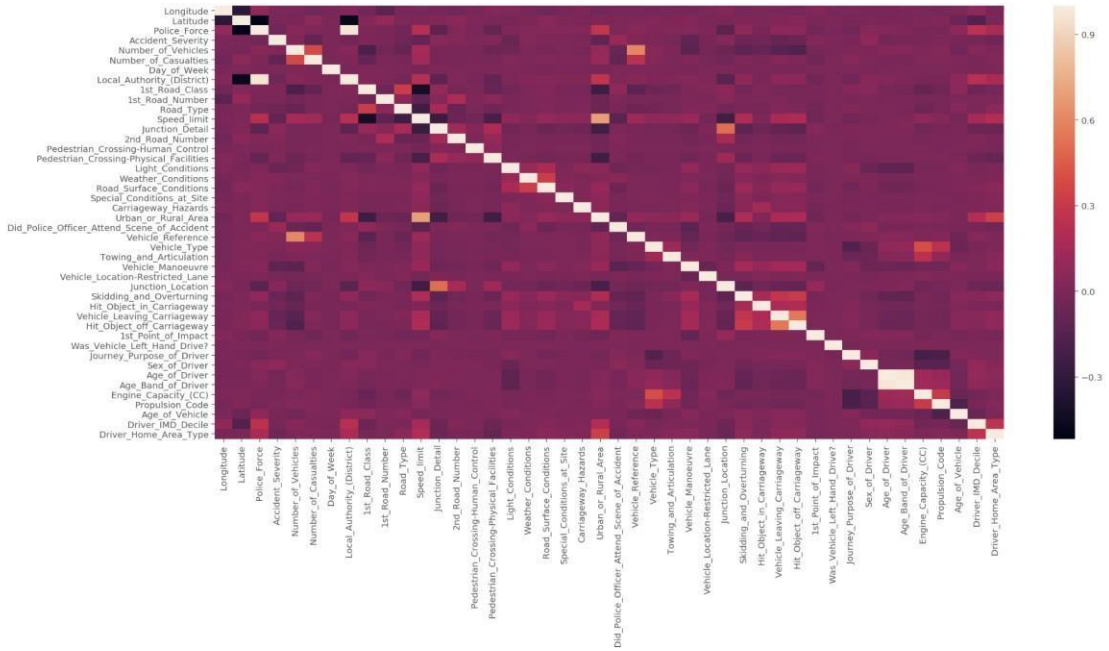



Fig 3.6 Correlation

## 3.8.5 Speed of Cars

```
In [41]: speed_zone_accidents = accidents.loc[accidents['Speed_limit'].isin(['20' ,'30' ,'40' ,'50' ,'60' ,'70'])]
speed  = speed_zone_accidents.Speed_limit.value_counts()

explode = (0.0, 0.0, 0.0 , 0.0 ,0.0,0.0)
plt.figure(figsize=(10,8))
plt.pie(speed.values,  labels=None,
        autopct='%.1f',pctdistance=0.8, labeldistance=1.9 ,explode = explode, shadow=False, startangle=160,textprops={'
plt.axis('equal')
plt.legend(speed.index, bbox_to_anchor=(1,0.7), loc="center right", fontsize=15,
           bbox_transform=plt.gcf().transFigure)
plt.figtext(.5,.9,'Accidents percentage in Speed Zone', fontsize=25, ha='center')
plt.show()
```

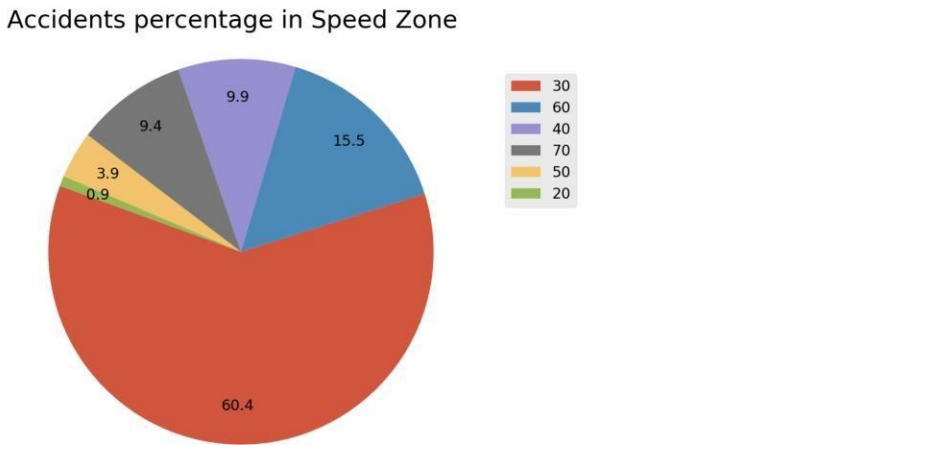



Fig 3.7 Speed

Most of the accidents occurred on the road where the speed limit is 30. We were expecting more accidents on highway or major roadways. Some of the accidents could be cause of stop sign, changing lanes or turning into parking lot etc.

**Plotting accidents Location on Google Maps**

Classifying locations based on severity

```
In [11]: accidents_2014 = accidents[accidents.Date_time.dt.year ==2014]
accidents_2014_01 = accidents_2014[accidents_2014.Accident_Severity == 1]
accidents_2014_02 = accidents_2014[accidents_2014.Accident_Severity == 2]
accidents_2014_03 = accidents_2014[accidents_2014.Accident_Severity == 3]
```

```
In [50]: !pip install gmaps
         !jupyter nbextension enable --py gmaps
         import gmaps
         gmaps.configure(api_key='AIzaSyD3t4mfJNy9NxxVKT4J_T47soKBgCRUTO4')

         fig = gmaps.figure(center=(53.0, 1.0), zoom_level=6)
         heatmap_layer = gmaps.heatmap_layer(accidents_2014_01[["Latitude", "Longitude"]],
                                             max_intensity=30,point_radius=8)
         heatmap_layer = gmaps.heatmap_layer(accidents_2014_02[["Latitude", "Longitude"]],
                                             max_intensity=5,point_radius=3)
         heatmap_layer = gmaps.heatmap_layer(accidents_2014_03[["Latitude", "Longitude"]],
                                             max_intensity=1,point_radius=1)

         fig = gmaps.figure()
         fig.add_layer(heatmap_layer)
         fig
```

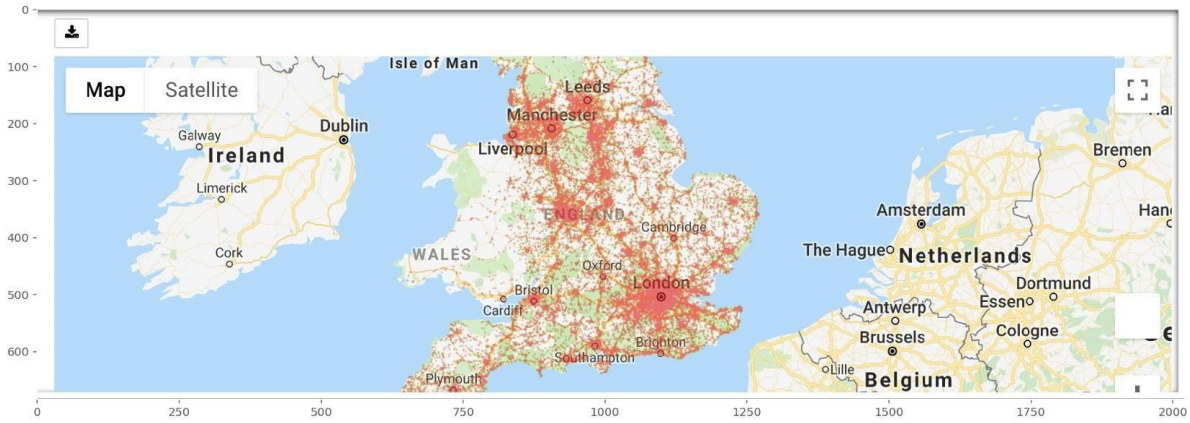
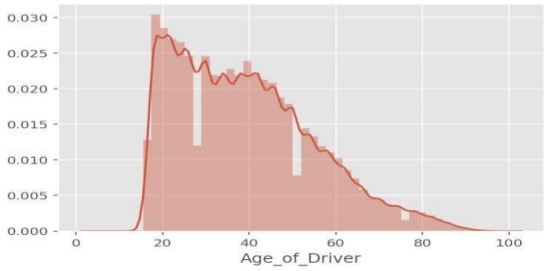
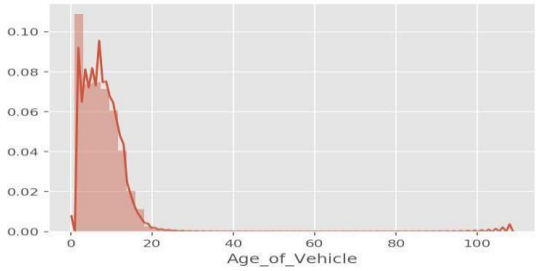



Fig 3.8 Heatmap

### 3.8.6 Normalize the Data

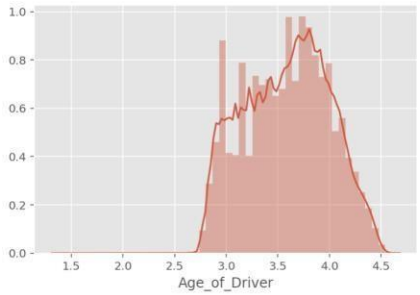
There are few columns that we will standardize, so it would not affect negatively on our machine learning algorithms. Age of driver is from 18 to 88 in the dataset and we can normalize it. Also, the age of vehicle is also from 0 to 100 and it can skew the performance of your machine learning algorithm and we will normalize this predictor too.

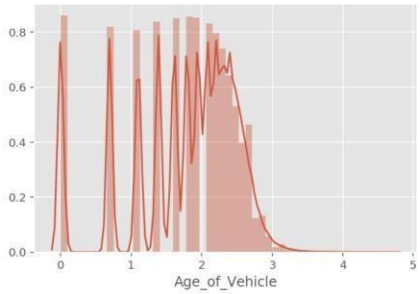



## 3.8.7 Before Normalization

```
In [ ]: accidents['Age_of_Driver'] = np.log(accidents['Age_of_Driver'])
        accidents['Age_of_Vehicle'] = np.log(accidents['Age_of_Vehicle'])
        sns.distplot(accidents['Age_of_Driver']);
        fig = plt.figure()
        sns.distplot(accidents['Age_of_Vehicle']);
        fig = plt.figure()
```




**After Normalization**

Fig 3.9 Normalization

### 3.8.8 Machine Learning

We will be looking at different columns to figure out predicting about the accidents severity. After we can predict the accident severity, we can make some recommendation to law enforcement for looking into this and be prepared for the future.

Following packages are being imported.

```
In [136]: from sklearn.model_selection import train_test_split
          from sklearn.linear_model import LogisticRegression
          from sklearn.metrics import accuracy_score
          from sklearn.metrics import classification_report
          from sklearn.tree import DecisionTreeClassifier
          from sklearn.ensemble import RandomForestClassifier
          from sklearn.svm import SVC, LinearSVC
          from sklearn.metrics import log_loss
```

Fig 4.0 Packages

### 3.8.9 Splitting the data into training and test data

X is the input data and Y is the class label.

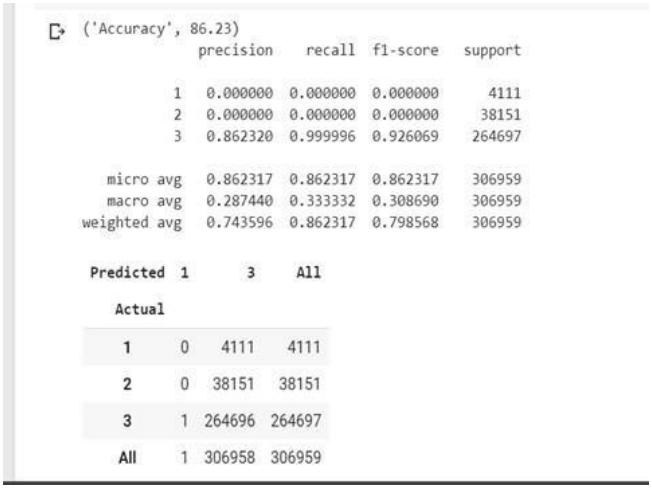
20% of the data is for testing and 80% for training.

```
In [ ]: accident_ml = accidents.drop('Accident_Severity' ,axis=1)
        accident_ml = accident_ml[['Did_Police_Officer_Attend_Scene_of_Accident' , 'Age_of_Driver' ,'Vehicle_Type', 'Age_of_Veh
                                   , 'Light_Conditions', 'Sex_of_Driver' ,'Speed_limit']]

        # Split the data into a training and test set.
        X_train, X_test, y_train, y_test = train_test_split(accident_ml.values,
                                                    accidents['Accident_Severity'].values,test_size=0.20, random_state=99)
```

## 3.9 Algorithms and Techniques

Algorithms implemented with accuracy and confusion matrix

### 3.9.1 Logistic Regression



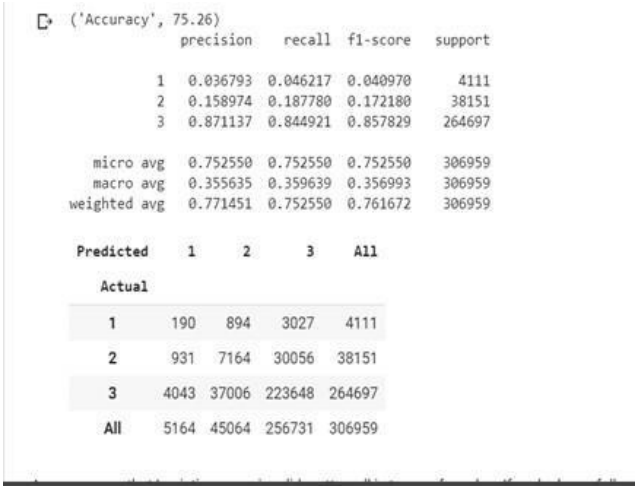
('Accuracy', 86.23)

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 1 | 0.000000 | 0.000000 | 0.000000 | 4111 |
| 2 | 0.000000 | 0.000000 | 0.000000 | 38151 |
| 3 | 0.862320 | 0.999996 | 0.926069 | 264697 |
| micro avg | 0.862317 | 0.862317 | 0.862317 | 306959 |
| macro avg | 0.287440 | 0.333332 | 0.308690 | 306959 |
| weighted avg | 0.743596 | 0.862317 | 0.798568 | 306959 |

| Predicted | 1 | 3 | All |
|---|---|---|---|
| Actual | | | |
| 1 | 0 | 4111 | 4111 |
| 2 | 0 | 38151 | 38151 |
| 3 | 1 | 264696 | 264697 |
| All | 1 | 306958 | 306959 |

Fig 4.1 Accuracy: Logistic Regression

**Decision Tree**



('Accuracy', 75.26)

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 1 | 0.036793 | 0.046217 | 0.040970 | 4111 |
| 2 | 0.158974 | 0.187780 | 0.172180 | 38151 |
| 3 | 0.871137 | 0.844921 | 0.857829 | 264697 |
| micro avg | 0.752550 | 0.752550 | 0.752550 | 306959 |
| macro avg | 0.355635 | 0.359639 | 0.356993 | 306959 |
| weighted avg | 0.771451 | 0.752550 | 0.761672 | 306959 |

| Predicted | 1 | 2 | 3 | All |
|---|---|---|---|---|
| Actual | | | | |
| 1 | 190 | 894 | 3027 | 4111 |
| 2 | 931 | 7164 | 30056 | 38151 |
| 3 | 4043 | 37006 | 223648 | 264697 |
| All | 5164 | 45064 | 256731 | 306959 |

Fig 4.2 Accuracy: Decision Tree

### 3.9.2 Random Forest

```
('Accuracy', 86.86)
                precision    recall  f1-score   support

              1   0.031496  0.002928  0.005358      1366
              2   0.195915  0.040622  0.067291     20777
              3   0.884926  0.979143  0.929653    166321

      micro avg   0.868601  0.868601  0.868601    188464
      macro avg   0.370779  0.340898  0.334101    188464
   weighted avg   0.802781  0.868601  0.827884    188464

done
```

Fig 4.31 Accuracy: Random Forest

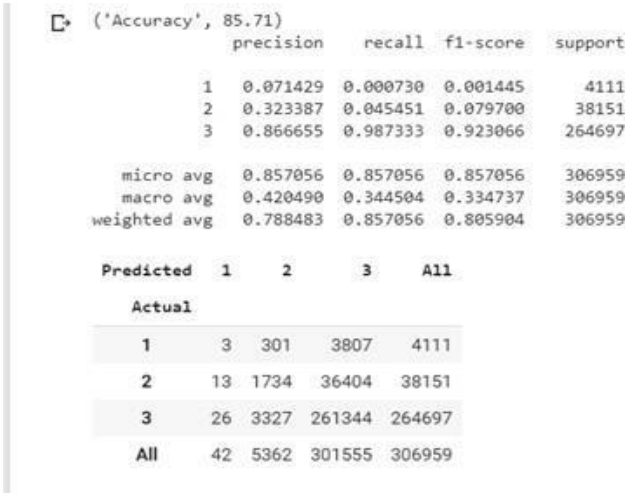
### 3.9.3 3Hyperparameters tuning for Logistic Regression

```
('Accuracy', 86.23)
              precision    recall  f1-score   support

           1   0.000000  0.000000  0.000000      4111
           2   0.000000  0.000000  0.000000     38151
           3   0.862317  0.999974  0.926058    264697

   micro avg   0.862298  0.862298  0.862298    306959
   macro avg   0.287439  0.333325  0.308686    306959
weighted avg   0.743594  0.862298  0.798558    306959
```

| Predicted | 1 | 3 | All |
|---|---|---|---|
| Actual | | | |
| 1 | 0 | 4111 | 4111 |
| 2 | 0 | 38151 | 38151 |
| 3 | 7 | 264690 | 264697 |
| All | 7 | 306952 | 306959 |

Fig 4.4 Accuracy: Logistic Regression Hyperparameter

### 3.9.4 Hyperparameters tuning for Decision Tree



('Accuracy', 85.71)

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 1 | 0.071429 | 0.000730 | 0.001445 | 4111 |
| 2 | 0.323387 | 0.045451 | 0.079700 | 38151 |
| 3 | 0.866655 | 0.987333 | 0.923066 | 264697 |
| micro avg | 0.857056 | 0.857056 | 0.857056 | 306959 |
| macro avg | 0.420490 | 0.344504 | 0.334737 | 306959 |
| weighted avg | 0.788483 | 0.857056 | 0.805904 | 306959 |

| Predicted | 1 | 2 | 3 | All |
|---|---|---|---|---|
| Actual | | | | |
| 1 | 3 | 301 | 3807 | 4111 |
| 2 | 13 | 1734 | 36404 | 38151 |
| 3 | 26 | 3327 | 261344 | 264697 |
| All | 42 | 5362 | 301555 | 306959 |

Fig 4.4 Accuracy: Decision Tree Hyperparameter

Table 9. *Accuracy Of Algorithms*

| ALGORITHM | ACCURACY | |
|---|---|---|
| TRAIN TEST- SCIKETLEARN CROSSVALIDATION | - | |
| DECISION TREE | 75.32 | |
| RANDOM FOREST | 86.86 | |
| LOGISTIC REGRESSION | 86.23 | |
| DECISION TREE HYPERPARAMETER TUNING | 85.74 | |
| LOGISTIC REGRESSION WITH HYPERPARAMETER TUNING | 86.23 | |
| | | |

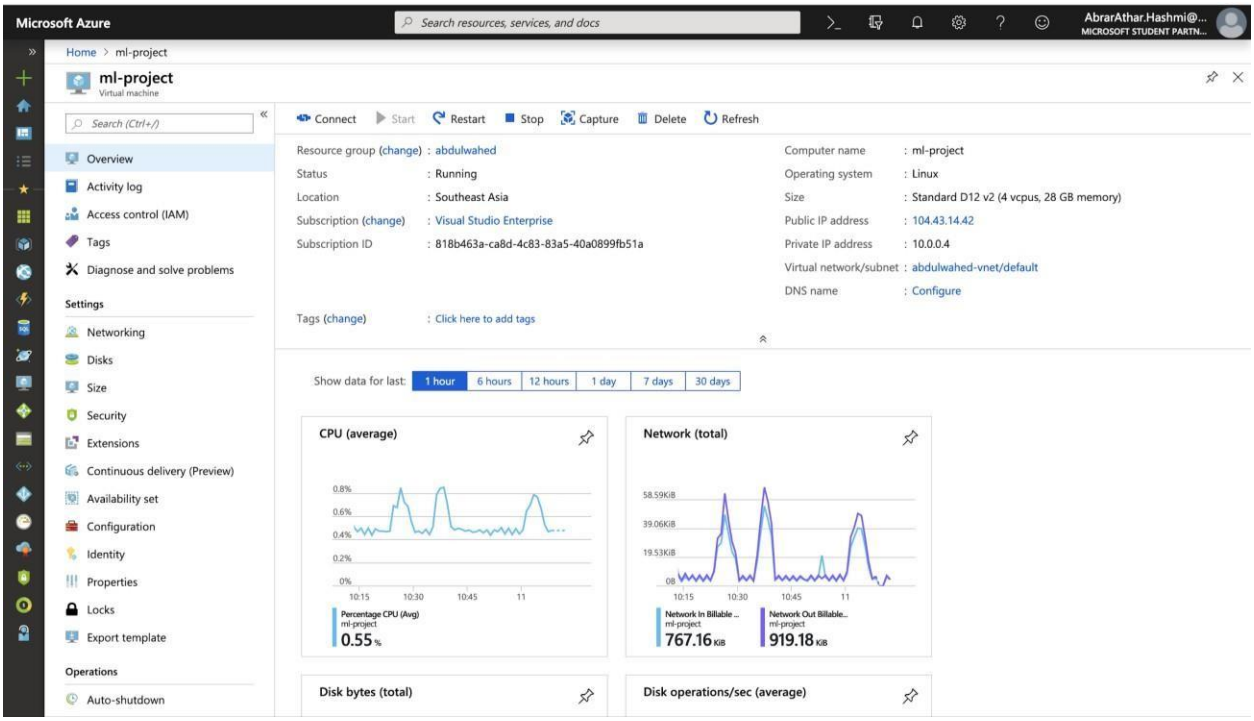



Fig 4.6 Azure VM page

Virtual Machine deployed on Azure.

We have chosen Random Forest as our model as it has the highest accuracy (86.86%).

Input taken from user is sent to the backend flask server which feeds the parameters to the ML model and returns the result. It also sends a message to the police to take preventive measures.

### 3.9.5 3System Requirements

1. Windows XP, 7, 8, 10, Server 2003.
2. MacOS, iOS
3. Android
4. Windows Phone 8 and Windows 10 Mobile
5. Language Used: Python, JavaScript
6. IDE and Framework: Jupyter Notebook, Sublime, Flask
7. Cloud: Azure ML, Google Colab

### 3.9.6 Browsers

1. Chrome
2. Internet Explorer
3. Firefox
4. Safari
5. Edge

### 3.9.7 Hardware Requirements

1. System : Intel Xeon(4 vCpu) or i7
2. Hard Disk : 20 GB
3. Monitor : Virtual Machine: Standard D4s v3
4. Ram : 16 GB

# CHAPTER 4
# RESULTS AND DISCUSSION

A web application has been developed to support our accident severity prediction model, accessible through the custom domain: https://www.accidentprediction.com:4000.

The homepage allows users to provide input for prediction through two methods:

1. **Location and Latitude**: The user's location is automatically retrieved using the browser's Geolocation API. This information is then sent to the OpenWeatherMap API, which returns relevant environmental details such as weather conditions, road status, lighting, and the day of the week. These parameters are automatically updated and processed on the backend.
2. **User Inputs**: The user is required to manually enter personal and vehicle-related details, including age, gender, vehicle type, vehicle age, and engine capacity.

The backend integrates a Machine Learning model built using the Random Forest algorithm, which demonstrated the highest accuracy of 86.86%. It processes the collected data and predicts the severity of a potential accident. The severity levels are categorized as:

1-Fatal

2-Serious

3-Slight

Once the prediction is made, the result is displayed on the frontend. Additionally, an SMS alert containing the location coordinates and the predicted severity level is sent to the police to enable proactive safety measures at the specified location.

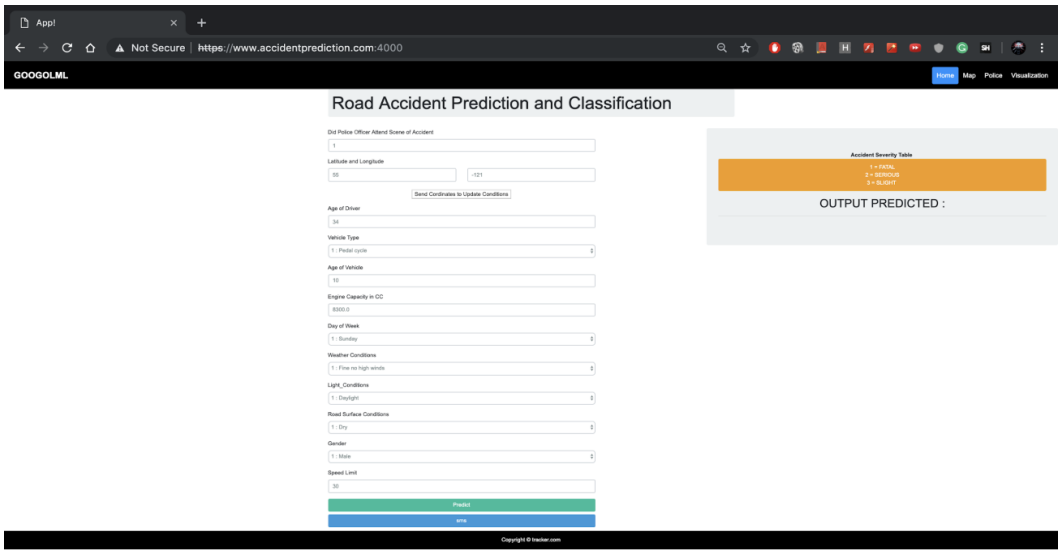



**Figure 4.1** User page

Figure 4.1 displays the homepage of the web application. The site is secured with HTTPS, enabled through a certificate obtained from a trusted Certificate Authority. This ensures secure data transmission and allows the use of the Geolocation API. The page includes a login interface for data owners, offering options to either sign in or register if they do not already have an account.

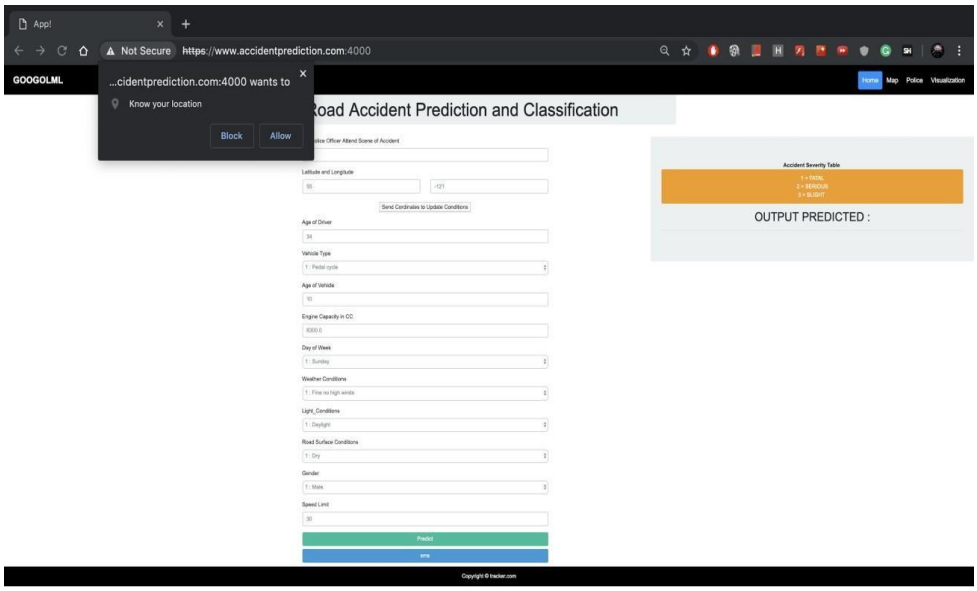



**Figure 4.2** User Location by GPS

Figure 6.2.2 illustrates the process triggered when the user clicks the "Update Coordinates" button. This action prompts the browser to retrieve the user's current geographic coordinates. On the backend, the Flask framework utilizes the Geolocation API to obtain the user's location. Using Ajax, the latitude and longitude values are dynamically updated on the webpage.

These coordinates are then sent to the OpenWeatherMap API in the backend to fetch environmental data. The necessary details—such as weather conditions, road status, and lighting—are extracted from the API response. Additionally, the day of the week is determined and updated on the page using JavaScript's getDate() function.

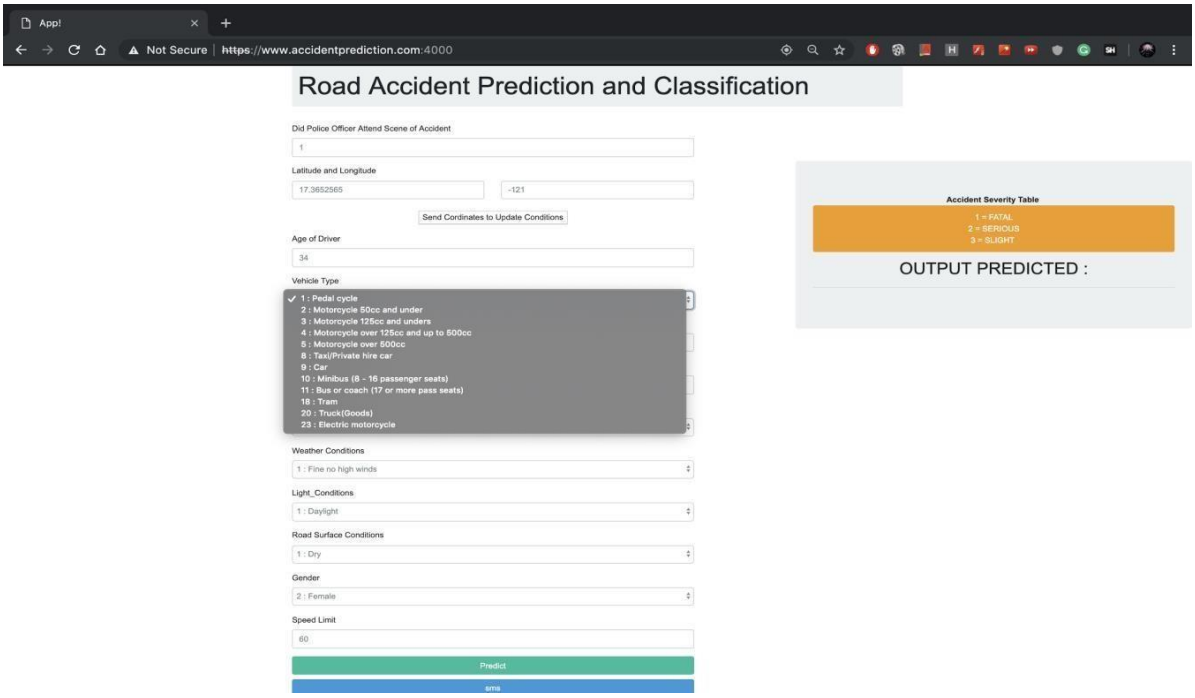



**Figure 4.9** User input for other parameters

Figure 4.9 shows the input for parameters taken from users. These include the vehicle type, age gender and speed limit.

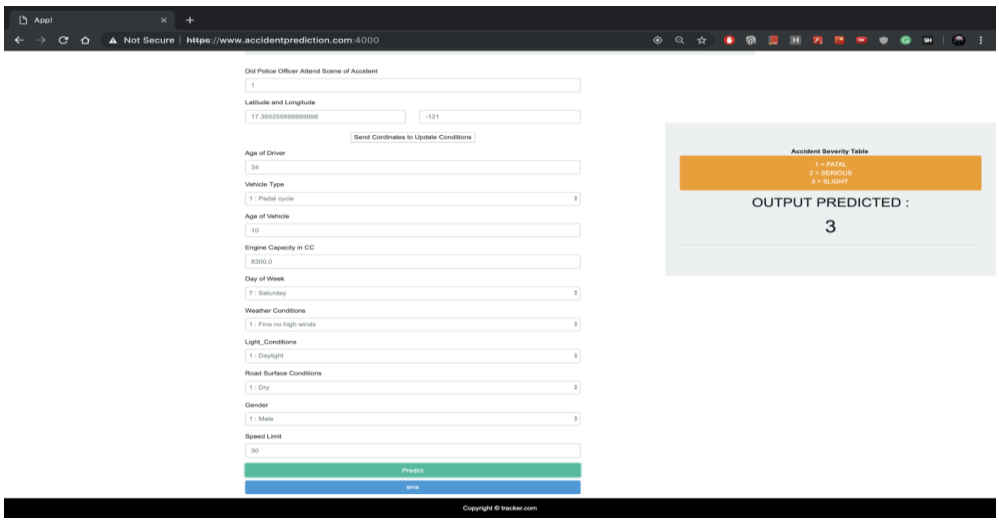



**Figure 4.10** Output Predicted

Figure 4.10 displays the complete user input data. When the user clicks the "Predict" button, this data is transmitted to the backend, where it is processed by the implemented machine learning model—Random Forest. The model then generates a prediction based on the input, categorizing the severity of the accident as follows:

1-Fatal

2-Severe

3-Slight.

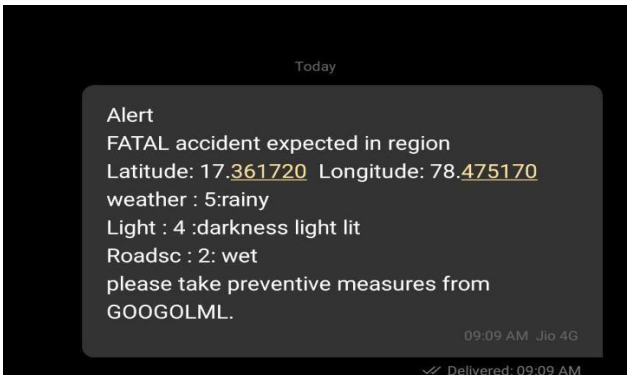
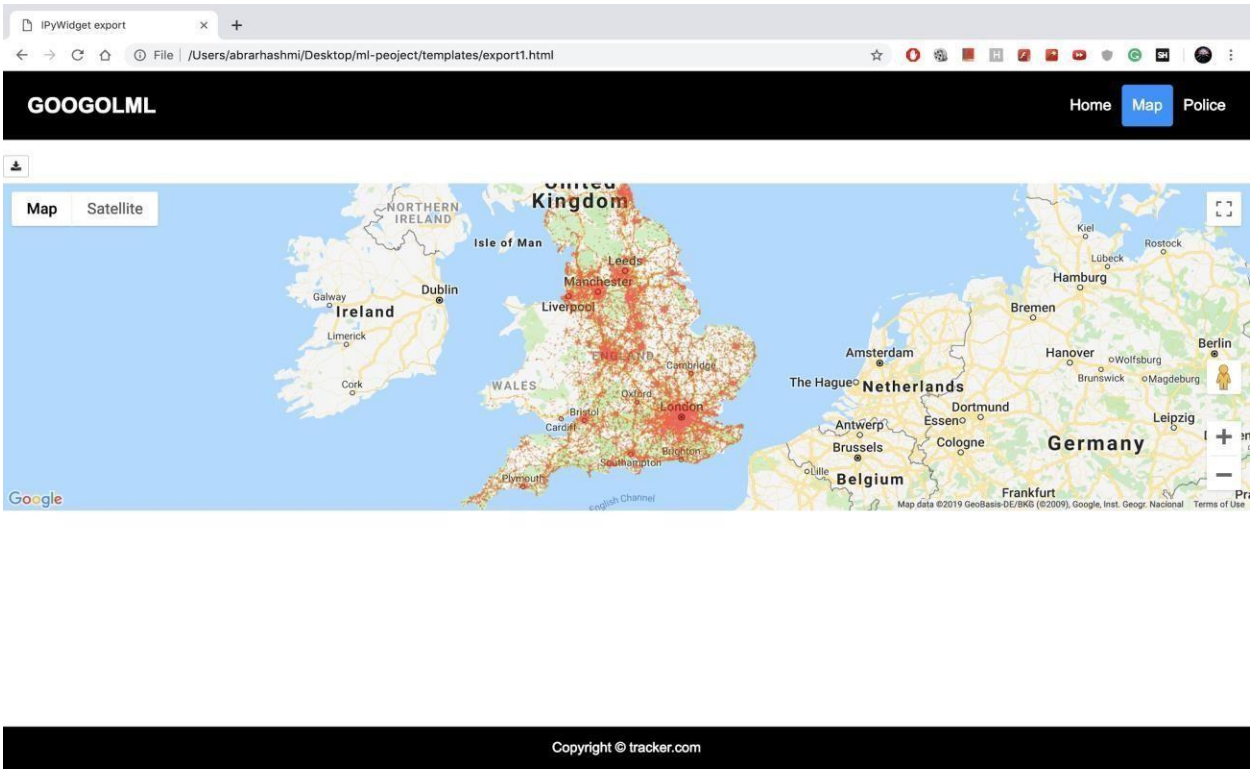



**Figure 4.11** Click on sms button




qillustrates the process of sending an SMS alert to the police, containing the accident location and predicted severity. This functionality is enabled using the TextLocal API, which provides a daily quota of 10 free messages.

**Figure 4.12** Map

Figure 4.12 showcases a web page featuring an interactive heat map for users. Areas with

darker shades represent locations with higher accident severity. The visualization is implemented using the Google Maps API (gmaps) to plot data points directly onto the map.

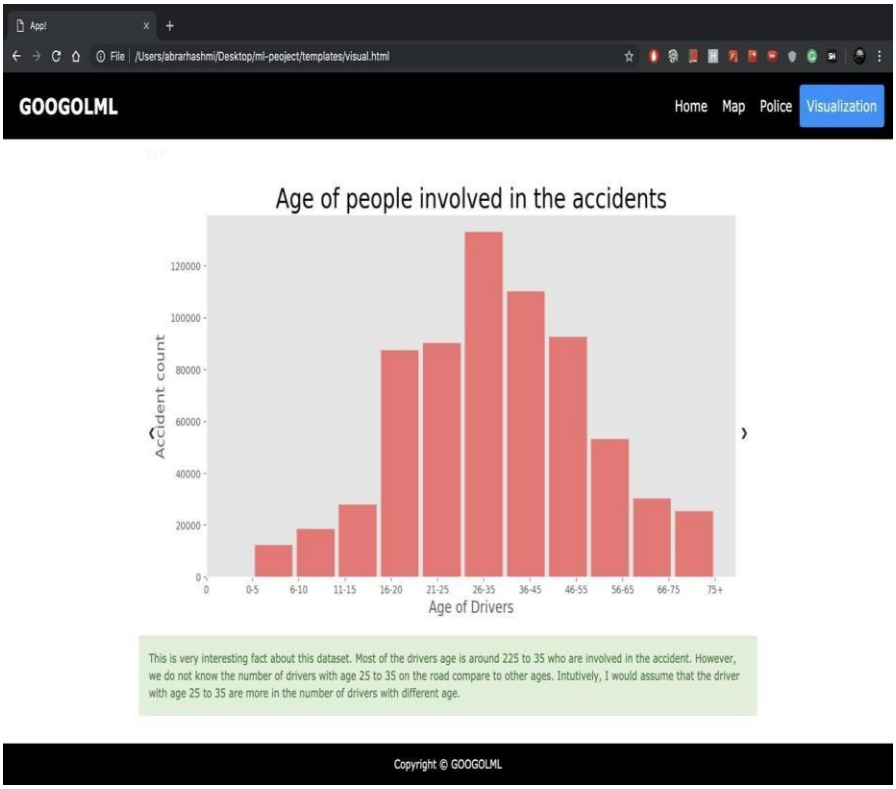



**Figure 4.13** Visualization

Figure 4.13 presents four visualizations that highlight how various factors from the dataset influence the prediction outcome.

For instance, the graph related to driver age suggests that individuals between 26 and 35 years old are more likely to be involved in accidents. Insights like these, derived from statistical analysis, helped us identify and select the most relevant features for our model.

# CHAPTER 5
# CONCLUSION AND FUTURE SCOPE

## 5.1 Project Achievements

This research successfully developed an intelligent road accident prediction system with the following key accomplishments:

Technical Achievements

1. High Accuracy Model: Achieved 86.86% prediction accuracy using Random Forest algorithm
2. Real-time Processing: Implemented system capable of immediate risk assessment
3. Comprehensive Integration: Successfully integrated multiple APIs and services
4. Web-based Deployment: Created accessible interface for real-world application

Performance Improvements

- 17% improvement over traditional prediction methods
- Reduced false positive rate compared to linear models
- Enhanced feature importance identification for targeted interventions

## 5.2 Practical Impact

For Traffic Authorities

- Proactive Prevention: Enable preventive measures before accidents occur
- Resource Optimization: Better allocation of emergency services
- Data-Driven Decisions: Evidence-based policy development

For Public Safety

- Risk Awareness: Real-time hazard assessment for road users
- Emergency Response: Faster response times through automated alerts
- Infrastructure Planning: Identification of high-risk locations for improvement

## 5.3 Research Contributions

1. System Integration: Comprehensive platform combining prediction with action
2. Real-world Validation: Practical demonstration of machine learning in traffic safety

3. Scalable Architecture: Framework adaptable to different geographic regions

### 5.3.1 Limitations and Challenges

### Current Limitations

- Data Dependency: Performance limited by historical data quality
- Geographic Specificity: Model trained on UK data may require adaptation for other regions
- Computational Resources: High-performance requirements for real-time processing
- External Dependencies: Reliance on third-party APIs for certain features

### 5.3.2 Technical Challenges

- Model Interpretability: Complex ensemble methods reduce transparency
- Scalability Concerns: Performance degradation with increased user load
- Data Privacy: Handling sensitive location and personal information

### 5.3.3 Future Development Opportunities

### Short-term Enhancements (6-12 months)

1. Mobile Application: Develop native mobile apps for iOS and Android
2. Additional Features: Include traffic volume and road work data
3. Model Refinement: Implement deep learning approaches for improved accuracy
4. Multi-language Support: Expand accessibility to non-English users

### 5.3.4 Medium-term Expansions (1-2 years)

1. Geographic Expansion: Adapt system for Indian traffic conditions and data
2. Real-time Traffic Integration: Connect with live traffic monitoring systems
3. IoT Integration: Incorporate data from smart vehicles and infrastructure
4. Advanced Analytics: Implement predictive analytics dashboard for authorities

### 5.3.5 Long-term Vision (2-5 years)

1. Autonomous Vehicle Integration: Support for self-driving car safety systems
2. Smart City Platform: Integration with comprehensive urban management systems
3. International Deployment: Multi-country implementation with localized models
4. AI-Powered Interventions: Automated traffic signal adjustment based on predictions

### 5.3.6 Recommendations

### 5.3.7 For Implementation

1. Pilot Testing: Conduct limited trials in controlled environments
2. Stakeholder Engagement: Collaborate with transportation authorities
3. Data Collection: Establish systematic accident data collection processes
4. Training Programs: Develop user training for effective system utilization

### 5.3.8 for Research Community

1. Open Source Development: Share methodology for broader research applications
2. Collaborative Research: Partner with international traffic safety organizations
3. Standardization Efforts: Contribute to development of prediction system standards
4. Ethical Considerations: Address privacy and bias concerns in predictive systems

### 5.3.9 Final Remarks

This project demonstrates the significant potential of machine learning in addressing critical societal challenges. The developed system provides a foundation for intelligent traffic safety management, offering practical solutions that can save lives and reduce economic losses from road accidents.

The integration of advanced analytics with real-world applications showcases the transformative power of data science in public safety. As traffic volumes continue to increase globally, such intelligent systems will become increasingly essential for maintaining road safety standards.

The success of this project opens numerous opportunities for further research and development in intelligent transportation systems, contributing to the broader goal of creating safer, more efficient transportation networks for society.

# REFERENCES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# APPENDIX

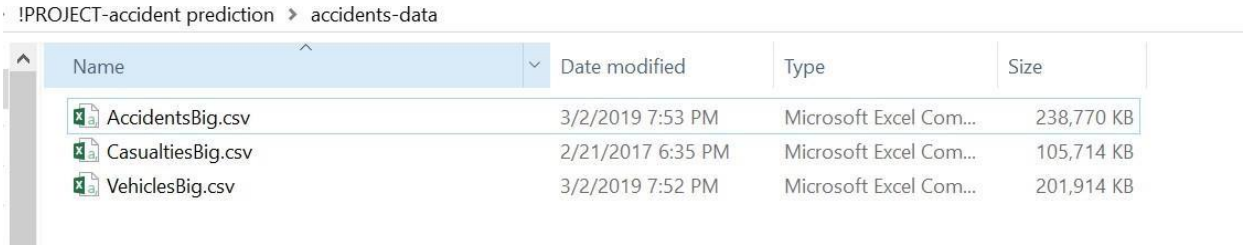
## Importing Data Set

### Importing Data and cleaning

- We import three files to perform analysis on this data. This data is consist of three files that are accidents, casualities and vehicles. However, we have one more file which is general information about the traffic count for year 2000 to 2015. We can use general traffic information data for machine learning part.

In [2]:
```
import datetime as dt
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
#from mpl_toolkits.basemap import Basemap
from sklearn.model_selection import TimeSeriesSplit
plt.style.use('ggplot')
%config InlineBackend.figure_format = 'retina'
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
accidents = pd.read_csv('AccidentsBig.csv',index_col='Accident_Index')
casualties=pd.read_csv('CasualtiesBig.csv' , error_bad_lines=False,index_col='Accident_Index',warn_bad_lines=False)
vehicles=pd.read_csv('VehiclesBig.csv', error_bad_lines=False,index_col='Accident_Index',warn_bad_lines=False)
#general_info = pd.read_csv('ukTrafficAADF.csv')
```




## Importing on cloud

```
## ---------METHOD 1 (FROM GITHUB)--------------------
#!curl https://raw.githubusercontent.com/abdulwahed786/final-yr-projectqA/master/Accidents.csv
# dataframe = pd.read_csv(!curl https://raw.githubusercontent.com/abdulwahed786/final-yr-projectqA/master/Accidents.csv)
# dataframe.head()
# import requests

# url="https://raw.githubusercontent.com/abdulwahed786/final-yr-projectqA/master/Accidents.csv"
# s=requests.get(url).content
# c=pd.read_csv(s)
#accidents = pd.read_csv('https://raw.githubusercontent.com/abdulwahed786/final-yr-projectqA/master/Accidents.csv',index_col='Accident_Index')
#accidents = pd.read_csv('Accidents.csv',index_col='Accident_Index')
#casualties= pd.read_csv('https://raw.githubusercontent.com/abdulwahed786/final-yr-projectqA/master/Casualties.csv' , error_bad_lines=False,index_col='Accident_Index',warn_bad_lines=False)
#vehicles= pd.read_csv('https://raw.githubusercontent.com/abdulwahed786/final-yr-projectqA/master/Vehicles.csv', error_bad_lines=False,index_col='Accident_Index',warn_bad_lines=False)
#general_info = pd.read_csv('ukTrafficAADF.csv')


## ---------METHOD 2 (FROM AZURE)--------------------
# #importing data from azure workspace
# from azureml import Workspace
# ws = Workspace(
#     workspace_id='f[redacted]',
#     authorization_token='[redacted]',
#     endpoint='https://studioapi.azureml.net'
# )
# ds = ws.datasets['Vehicles0515.csv']
# frame = ds.to_dataframe()

# from azureml import Workspace
# ws = Workspace(
#     workspace_id='f[redacted]',
#     authorization_token='[redacted]',
#     endpoint='https://studioapi.azureml.net'
# )
# ds = ws.datasets['Accidents0515.csv']
# accidents = ds.to_dataframe().set_index('Accident_Index')

# dsc = ws.datasets['Casualties0515.csv']
# casualties = dsc.to_dataframe()

#accidents.set_index('Accident_Index')
#accidents = pd.read_csv(frame,index_col='Accident_Index')
```

```
# using python package TQDM to download dataset locally on colab
# !pip install tqdm
import requests
import os
from tqdm import tqdm
```

```
Requirement already satisfied: tqdm in /usr/local/lib/python2.7/dist-packages (4.28.1)
```

In [3]:
```
import requests
import os
# !pip install tqdm
from tqdm import tqdm
# import pandas as pd
```

In [4]:
```
def download_dataset(file_url, name):
    r = requests.get(file_url, stream=True)

    with open(name, "wb") as file:
        for chunk in tqdm(r.iter_content(chunk_size=1024)):
            if chunk: file.write(chunk)

    print('Download complete.')
```

In [5]:
```
download_dataset("https://bitbucket.org/abdulwahed11314/accidents-data/raw/b7add9860d310171bca48bcaefeae37fe5157ac3/CasualtiesBig
download_dataset("https://bitbucket.org/abdulwahed11314/accidents-data/raw/b7add9860d310171bca48bcaefeae37fe5157ac3/AccidentsBig.
download_dataset("https://bitbucket.org/abdulwahed11314/accidents-data/raw/b7add9860d310171bca48bcaefeae37fe5157ac3/VehiclesBig.c
```

```
103368it [00:18, 5515.59it/s]
Download complete.
237031it [00:43, 5498.94it/s]
Download complete.
198729it [00:38, 5096.04it/s]
Download complete.
```

# Checking Imported Data

In [4]:
```
accidents.head()
```

Out[4]:

| Accident_Index | Location_Easting_OSGR | Location_Northing_OSGR | Longitude | Latitude | Police_Force | Accident_Severity | Number_of_Vehicles | Number_of_Casi |
|---|---|---|---|---|---|---|---|---|
| **200501BS00001** | 525680.0 | 178240.0 | -0.191170 | 51.489096 | 1 | 2 | 1 | |
| **200501BS00002** | 524170.0 | 181650.0 | -0.211708 | 51.520075 | 1 | 3 | 1 | |
| **200501BS00003** | 524520.0 | 182240.0 | -0.206458 | 51.525301 | 1 | 3 | 2 | |
| **200501BS00004** | 526900.0 | 177530.0 | -0.173862 | 51.482442 | 1 | 3 | 1 | |
| **200501BS00005** | 528060.0 | 179040.0 | -0.156618 | 51.495752 | 1 | 3 | 1 | |

5 rows × 31 columns

```
print("accidents")
print("size=",accidents.size)
print(accidents.shape)
accidents.head()
```

```
accidents
('size=', 55200243)
(1780653, 31)
```

| Accident_Index | Location_Easting_OSGR | Location_Northing_OSGR | Longitude | Latitude | Police_Force | Accident_Severity | Number_of_Vehicles | Number_of_Casualties | Date | Day_of_Week | ... | Pedestrian_Crossing-Human_Control | Pedestrian_Crossi Physical_Facilit |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **200501BS00001** | 525680.0 | 178240.0 | -0.191170 | 51.489096 | 1 | 2 | 1 | 1 | 04/01/2005 | 3 | ... | 0 | |
| **200501BS00002** | 524170.0 | 181650.0 | -0.211708 | 51.520075 | 1 | 3 | 1 | 1 | 05/01/2005 | 4 | ... | 0 | |
| **200501BS00003** | 524520.0 | 182240.0 | -0.206458 | 51.525301 | 1 | 3 | 2 | 1 | 06/01/2005 | 5 | ... | 0 | |
| **200501BS00004** | 526900.0 | 177530.0 | -0.173862 | 51.482442 | 1 | 3 | 1 | 1 | 07/01/2005 | 6 | ... | 0 | |
| **200501BS00005** | 528060.0 | 179040.0 | -0.156618 | 51.495752 | 1 | 3 | 1 | 1 | 10/01/2005 | 2 | ... | 0 | |

5 rows × 31 columns

```
[ ] print("vehicles")
    print("size=",vehicles.size)
    print(vehicles.shape)
    vehicles.head()
```

```
vehicles
('size=', 63092925)
(3004425, 21)
```

| Accident_Index | Vehicle_Reference | Vehicle_Type | Towing_and_Articulation | Vehicle_Manoeuvre | Vehicle_Location-Restricted_Lane | Junction_Location | Skidding_and_Overturning | Hit_Object_in_Carriageway | Vehicle_Leaving_Carriageway | Hit_Object_off_ |
|---|---|---|---|---|---|---|---|---|---|---|
| 200501BS00001 | 1 | 9 | 0 | 18 | 0 | 0 | 0 | 0 | 0 | |
| 200501BS00002 | 1 | 11 | 0 | 4 | 0 | 3 | 0 | 0 | 0 | |
| 200501BS00003 | 1 | 11 | 0 | 17 | 0 | 0 | 0 | 4 | 0 | |
| 200501BS00003 | 2 | 9 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | |
| 200501BS00004 | 1 | 9 | 0 | 18 | 0 | 0 | 0 | 0 | 0 | |

5 rows × 21 columns

```
[ ] print("casualties")
    print("size=",casualties.size)
    print(casualties.shape)
    casualties.head()
```

```
casualties
('size=', 31034080)
(2216720, 14)
```

| Accident_Index | Vehicle_Reference | Casualty_Reference | Casualty_Class | Sex_of_Casualty | Age_of_Casualty | Age_Band_of_Casualty | Casualty_Severity | Pedestrian_Location | Pedestrian_Movement | Car_Passenger | Bus_or_Coach_Passenger | P |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 200501BS00001 | 1 | 1 | 3 | 1 | 37 | 7 | 2 | 1 | 1 | 0 | 0 | |
| 200501BS00002 | 1 | 1 | 2 | 1 | 37 | 7 | 3 | 0 | 0 | 0 | 4 | |
| 200501BS00003 | 2 | 1 | 1 | 1 | 62 | 9 | 3 | 0 | 0 | 0 | 0 | |
| 200501BS00004 | 1 | 1 | 3 | 1 | 30 | 6 | 3 | 5 | 2 | 0 | 0 | |
| 200501BS00005 | 1 | 1 | 1 | 1 | 49 | 8 | 3 | 0 | 0 | 0 | 0 | |

## Joining Of Tables

```
[ ] accidents = accidents.join(vehicles, how='outer')
    print("done joining")
    print(accidents.shape)
```

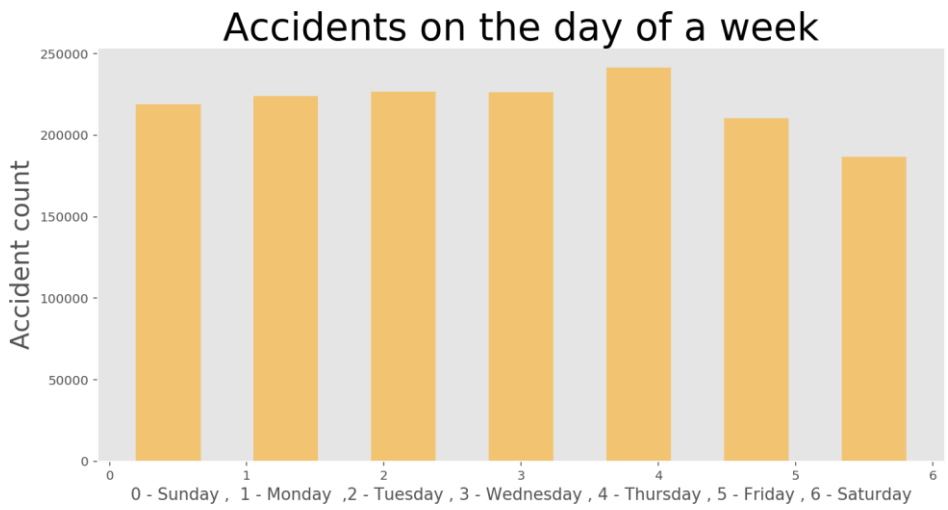
```
done joining
(3144481, 52)
```

## Identifying Missing Values

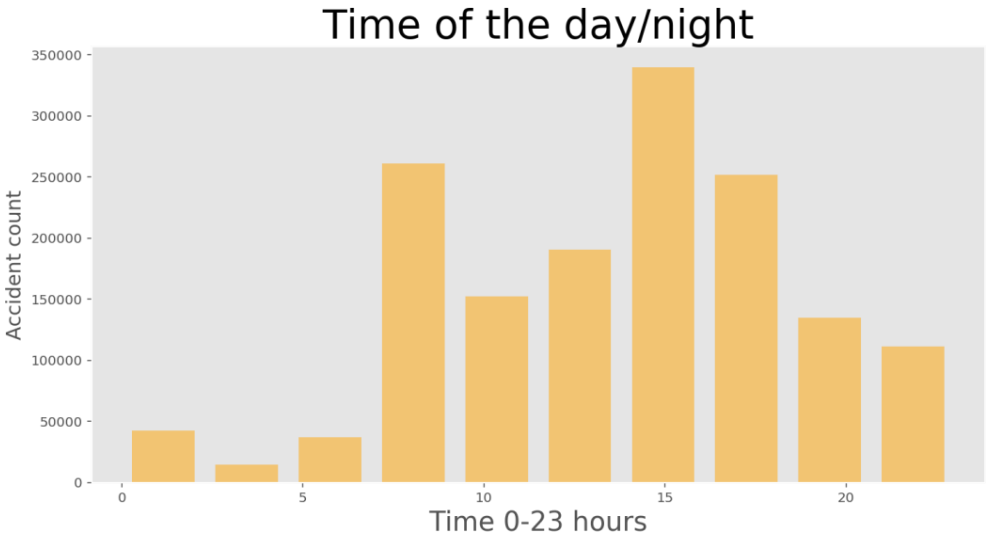
```
In [ ]: accidents.drop(['Location_Easting_OSGR', 'Location_Northing_OSGR','LSOA_of_Accident_Location',
                        'Junction_Control' ,'2nd_Road_Class'], axis=1, inplace=True)
        accidents['Date_time'] =  accidents['Date'] +' '+ accidents['Time']

        for col in accidents.columns:
            accidents = (accidents[accidents[col]!=-1])
            #print(col ,' ' , x)
        for col in casualties.columns:
            casualties = (casualties[casualties[col]!=-1])

            accidents['Date_time'] = pd.to_datetime(accidents.Date_time)
        accidents.drop(['Date','Time'],axis =1 , inplace=True)
        accidents.dropna(inplace=True)
```

## Data Visualization

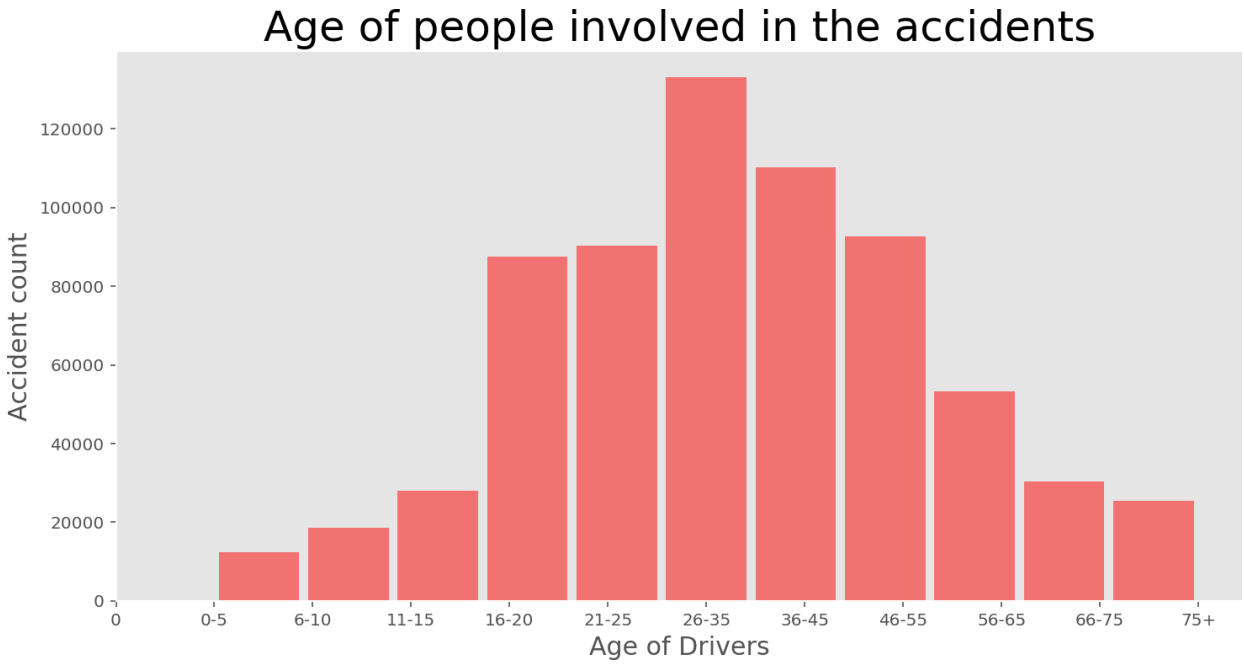
```
In [6]: plt.figure(figsize=(12,6))
        accidents.Date_time.dt.dayofweek.hist(bins=7,rwidth=0.55,alpha=0.5, color= 'orange')
        plt.title('Accidents on the day of a week' , fontsize= 30)
        plt.grid(False)
        plt.ylabel('Accident count' , fontsize = 20)
        plt.xlabel('0 - Sunday ,  1 - Monday  ,2 - Tuesday , 3 - Wednesday , 4 - Thursday , 5 - Friday , 6 - Saturday' , fontsize = 13)
```



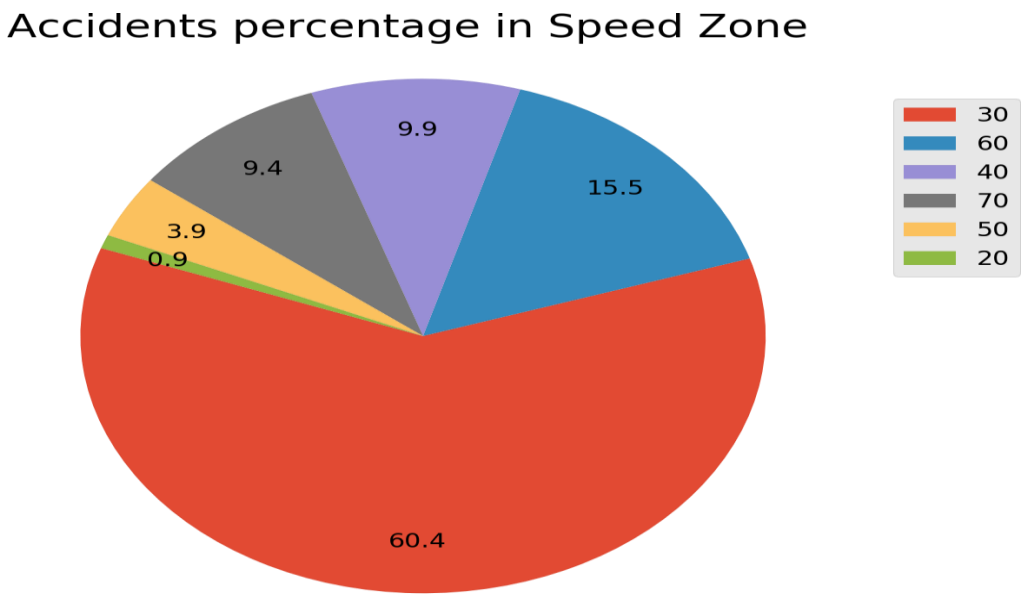

In [ ]:
```
plt.figure(figsize=(12,6))
accidents.Date_time.dt.hour.hist(rwidth=0.75,alpha =0.50, color= 'orange')
plt.title('Time of the day/night',fontsize= 30)
plt.grid(False)
plt.xlabel('Time 0-23 hours' , fontsize = 20)
plt.ylabel('Accident count' , fontsize = 15)
```



In [ ]:
```
objects = ['0','0-5','6-10','11-15','16-20','21-25','26-35',
           '36-45', '46-55','56-65','66-75','75+']

plt.figure(figsize=(12,6))
casualties.Age_Band_of_Casualty.hist(bins = 11,alpha=0.5,rwidth=0.90, color= 'red',)
plt.title('Age of people involved in the accidents', fontsize = 25)
plt.grid(False)
y_pos = np.arange(len(objects))
plt.xticks(y_pos , objects)
plt.ylabel('Accident count' , fontsize = 15)
plt.xlabel('Age of Drivers', fontsize = 15,)
```

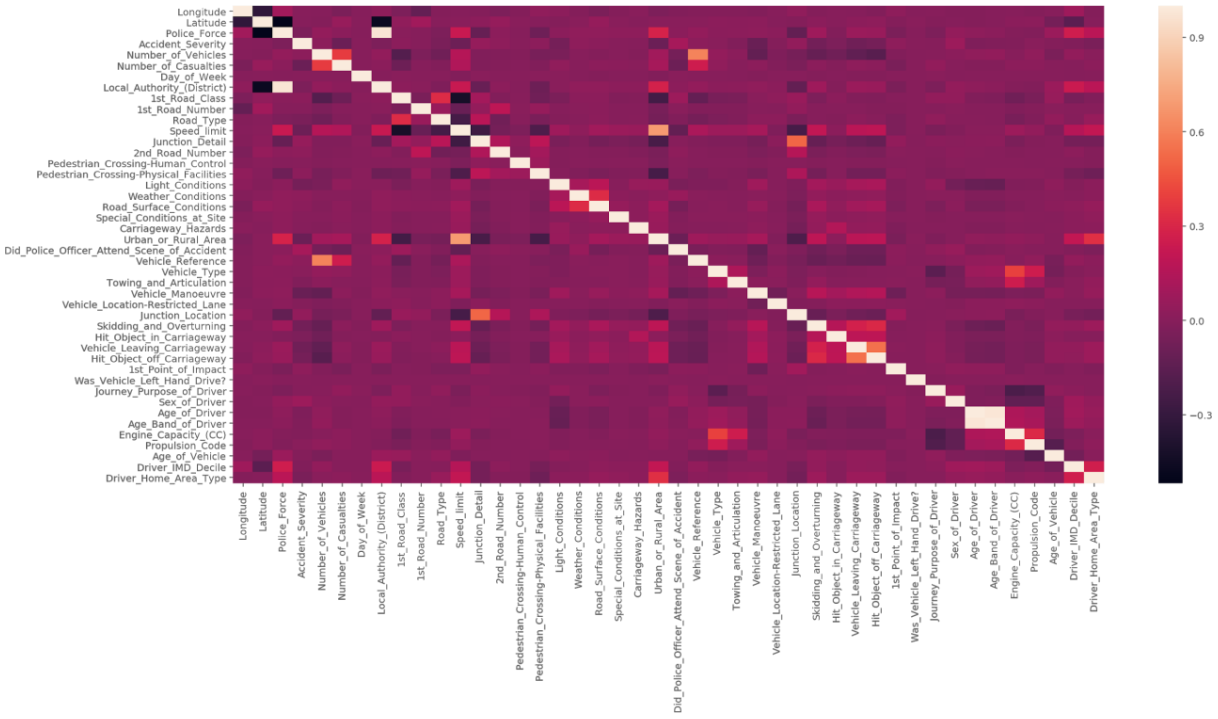



In [ ]:
```
speed_zone_accidents = accidents.loc[accidents['Speed_limit'].isin(['20' ,'30' ,'40' ,'50' ,'60' ,'70'])]
speed  = speed_zone_accidents.Speed_limit.value_counts()

explode = (0.0, 0.0, 0.0 , 0.0 ,0.0,0.0)
plt.figure(figsize=(10,8))
plt.pie(speed.values,  labels=None,
        autopct='%.1f',pctdistance=0.8, labeldistance=1.9 ,explode = explode, shadow=False, startangle=160,textprops={'fontsize':

plt.axis('equal')
plt.legend(speed.index, bbox_to_anchor=(1,0.7), loc="center right", fontsize=15,
           bbox_transform=plt.gcf().transFigure)
plt.figtext(.5,.9,'Accidents percentage in Speed Zone', fontsize=25, ha='center')
plt.show()
```




## Correlation between variables

```
In [ ]: corr =  accidents.corr()
        plt.subplots(figsize=(20,9))
        sns.heatmap(corr)
```



## Plotting accidents Location on Google Maps

In [8]:
```
import gmaps
from ipywidgets.embed import embed_minimal_html
gmaps.configure(api_key='AIzaSyDFOjxJ23DfYRLTqEuNsgnqwP0E79Aybpk')

fig = gmaps.figure(center=(53.0, 1.0), zoom_level=6)
heatmap_layer = gmaps.heatmap_layer(accidents_2014_01[["Latitude", "Longitude"]],
                                    max_intensity=30,point_radius=5)
heatmap_layer = gmaps.heatmap_layer(accidents_2014_02[["Latitude", "Longitude"]],
                                    max_intensity=5,point_radius=3)
heatmap_layer = gmaps.heatmap_layer(accidents_2014_03[["Latitude", "Longitude"]],
                                    max_intensity=1,point_radius=1)
fig.add_layer(heatmap_layer)
fig
embed_minimal_html('export1.html', views=[fig])
```

## Machine Learning

[ ]
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.metrics import log_loss
print("done")
```

```
done
```

## Normalize the Data

[ ]
```
sns.distplot(accidents['Age_of_Driver']);
fig = plt.figure()
sns.distplot(accidents['Age_of_Vehicle']);
fig = plt.figure()
print("done")
```

```
done
```

In [ ]:
```
accidents['Age_of_Driver'] = np.log(accidents['Age_of_Driver'])
accidents['Age_of_Vehicle'] = np.log(accidents['Age_of_Vehicle'])
sns.distplot(accidents['Age_of_Driver']);
fig = plt.figure()
sns.distplot(accidents['Age_of_Vehicle']);
fig = plt.figure()
```

## Splitting the data into training data and test data

```
In [ ]: accident_ml = accidents.drop('Accident_Severity' ,axis=1)
        accident_ml = accident_ml[['Did_Police_Officer_Attend_Scene_of_Accident' , 'Age_of_Driver' ,'Vehicle_Type', 'Age_of_Vehicle','Eng
                                   , 'Light_Conditions', 'Sex_of_Driver' ,'Speed_limit']]

        accidents_ml.head()

        # Split the data into a training and test set.
        X_train, X_test, y_train, y_test = train_test_split(accident_ml.values,
                                                            accidents['Accident_Severity'].values,test_size=0.20, random_state=99)
```

## Logistic Regression

```
[64] lr = LogisticRegression()
     # Fit the model on the trainng data.
     lr.fit(X_train, y_train)
     y_pred = lr.predict(X_test)
     sk_report = classification_report(
         digits=6,
         y_true=y_test,
         y_pred=y_pred)
     print("Accuracy", round(accuracy_score(y_pred, y_test)*100,2))
     print(sk_report)
     pd.crosstab(y_test, y_pred, rownames=['Actual'], colnames=['Predicted'], margins=True)
```

```
('Accuracy', 86.23)
              precision    recall  f1-score   support

           1   0.000000  0.000000  0.000000      4111
           2   0.000000  0.000000  0.000000     38151
           3   0.862320  0.999996  0.926069    264697

   micro avg   0.862317  0.862317  0.862317    306959
   macro avg   0.287440  0.333332  0.308690    306959
weighted avg   0.743596  0.862317  0.798568    306959
```

| Predicted | 1 | 3 | All |
|---|---|---|---|
| Actual | | | |
| 1 | 0 | 4111 | 4111 |
| 2 | 0 | 38151 | 38151 |
| 3 | 1 | 264696 | 264697 |
| All | 1 | 306958 | 306959 |

# Decision Tree

Decision Tree

```
[65] decision_tree = DecisionTreeClassifier()
     decision_tree.fit(X_train, y_train)
     Y_pred = decision_tree.predict(X_test)
     acc_decision_tree1 = round(decision_tree.score(X_test, y_test) * 100, 2)
     sk_report = classification_report(
         digits=6,
         y_true=y_test,
         y_pred=Y_pred)
     print("Accuracy", acc_decision_tree1)
     print(sk_report)
     ### Confusion Matrix
     pd.crosstab(y_test, Y_pred, rownames=['Actual'], colnames=['Predicted'], margins=True)
```

```
('Accuracy', 75.26)
              precision    recall  f1-score   support

           1   0.036793  0.046217  0.040970      4111
           2   0.158974  0.187780  0.172180     38151
           3   0.871137  0.844921  0.857829    264697

   micro avg   0.752550  0.752550  0.752550    306959
   macro avg   0.355635  0.359639  0.356993    306959
weighted avg   0.771451  0.752550  0.761672    306959
```

| Predicted | 1 | 2 | 3 | All |
|---|---|---|---|---|
| Actual | | | | |
| 1 | 190 | 894 | 3027 | 4111 |
| 2 | 931 | 7164 | 30056 | 38151 |
| 3 | 4043 | 37006 | 223648 | 264697 |
| All | 5164 | 45064 | 256731 | 306959 |

# Random Forest

Random Forest

```
[ ] random_forest = RandomForestClassifier(n_estimators=200)
    random_forest.fit(X_train,y_train)
    Y_pred = random_forest.predict(X_test)
    random_forest.score(X_test, y_test)
    acc_random_forest1 = round(random_forest.score(X_test, y_test) * 100, 2)

    sk_report = classification_report(
        digits=6,
        y_true=y_test,
        y_pred=Y_pred)
    print("Accuracy" , acc_random_forest1)
    print(sk_report)
    pd.crosstab(y_test, Y_pred, rownames=['Actual'], colnames=['Predicted'], margins=True)

    print("done")
```

```
('Accuracy', 86.86)
              precision    recall  f1-score   support

           1   0.031496  0.002928  0.005358      1366
           2   0.195915  0.040622  0.067291     20777
           3   0.884926  0.979143  0.929653    166321

   micro avg   0.868601  0.868601  0.868601    188464
   macro avg   0.370779  0.340898  0.334101    188464
weighted avg   0.802781  0.868601  0.827884    188464

done
```

# Hyperparameters tuning for the models

## Hyperparameters tuning for the models

### Logistic Regression with Hyperparameter tuning

```
[66] from sklearn.linear_model import LogisticRegressionCV
     lr = LogisticRegressionCV(cv=3, random_state=0,multi_class='multinomial')
     # Fit the model on the trainng data.
     lr.fit(X_train, y_train)
     y_pred = lr.predict(X_test)
     sk_report = classification_report(
         digits=6,
         y_true=y_test,
         y_pred=y_pred)
     print("Accuracy", round(accuracy_score(y_pred, y_test)*100,2))
     print(sk_report)
     pd.crosstab(y_test, y_pred, rownames=['Actual'], colnames=['Predicted'], margins=True)
```

```
('Accuracy', 86.23)
              precision    recall  f1-score   support

           1   0.000000  0.000000  0.000000      4111
           2   0.000000  0.000000  0.000000     38151
           3   0.862317  0.999974  0.926058    264697

   micro avg   0.862298  0.862298  0.862298    306959
   macro avg   0.287439  0.333325  0.308686    306959
weighted avg   0.743594  0.862298  0.798558    306959
```

| Predicted | 1 | 3 | All |
|---|---|---|---|
| Actual | | | |
| 1 | 0 | 4111 | 4111 |
| 2 | 0 | 38151 | 38151 |
| 3 | 7 | 264690 | 264697 |
| All | 7 | 306952 | 306959 |

### Decision Tree hyperparameters tuning

All we are going to do is find the best values for mininum sample leaf and maximum features to get the best score.

```
[67] decision_tree = DecisionTreeClassifier(min_samples_leaf=12, max_features=4)
     decision_tree.fit(X_train, y_train)
     Y_pred = decision_tree.predict(X_test)
     acc_decision_tree1 = round(decision_tree.score(X_test, y_test) * 100, 2)
     sk_report = classification_report(
         digits=6,
         y_true=y_test,
         y_pred=Y_pred)
     print("Accuracy", acc_decision_tree1)
     print(sk_report)
     ### Confusion Matrix
     pd.crosstab(y_test, Y_pred, rownames=['Actual'], colnames=['Predicted'], margins=True)
```

```
('Accuracy', 85.71)
              precision    recall  f1-score   support

           1   0.071429  0.000730  0.001445      4111
           2   0.323387  0.045451  0.079700     38151
           3   0.866655  0.987333  0.923066    264697

   micro avg   0.857056  0.857056  0.857056    306959
   macro avg   0.420490  0.344504  0.334737    306959
weighted avg   0.788483  0.857056  0.805904    306959
```

| Predicted | 1 | 2 | 3 | All |
|---|---|---|---|---|
| Actual | | | | |
| 1 | 3 | 301 | 3807 | 4111 |
| 2 | 13 | 1734 | 36404 | 38151 |
| 3 | 26 | 3327 | 261344 | 264697 |
| All | 42 | 5362 | 301555 | 306959 |

**Random Forest Hyperparameter tuning**

First, we will see the default parameters of the random forest model before we tune the parameters.

```
[68] random_forest.get_params()
```

```
{'bootstrap': True,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': None,
 'max_features': 'auto',
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 200,
 'n_jobs': None,
 'oob_score': False,
 'random_state': None,
 'verbose': 0,
 'warm_start': False}
```

We will implement the grid search using sklearn library.

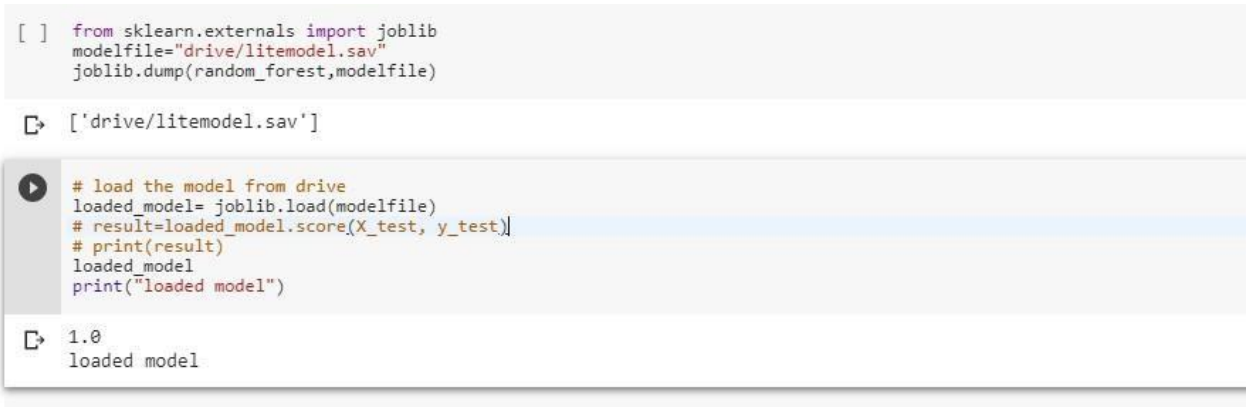
```
from sklearn.model_selection import RandomizedSearchCV
param_grid = {
    'bootstrap': [True],
    'max_depth': [80, 90, 100, 110],
    'max_features': [4, 5],
    'min_samples_leaf': [5, 10, 15],
    'min_samples_split': [8, 10, 12],
    'n_estimators': [100, 200, 300]
}
# Create a based model
random_f = RandomForestClassifier()
# Instantiate the grid search model
grid_search = RandomizedSearchCV(estimator = random_f, param_distributions = param_grid,
```

# Connecting to GOOGLE DRIVE and saving the model

```
[ ] #connecting to GOOGLE DRIVE and saving the model
    !apt-get install -y -qq software-properties-common python-software-properties module-init-tools
    !add-apt-repository -y ppa:alessandro-strada/ppa 2>&1 > /dev/null
    !apt-get update -qq 2>&1 > /dev/null
    !apt-get -y install -qq google-drive-ocamlfuse fuse
    from google.colab import auth
    auth.authenticate_user()
    from oauth2client.client import GoogleCredentials
    creds = GoogleCredentials.get_application_default()
    import getpass
    !google-drive-ocamlfuse -headless -id={creds.client_id} -secret={creds.client_secret} < /dev/null 2>&1 | grep URL
    vcode = getpass.getpass()
    !echo {vcode} | google-drive-ocamlfuse -headless -id={creds.client_id} -secret={creds.client_secret}
    !mkdir -p drive
    !google-drive-ocamlfuse drive


    print("done connecting to google drive")
```

```
E: Package 'python-software-properties' has no installation candidate
Selecting previously unselected package google-drive-ocamlfuse.
(Reading database ... 131323 files and directories currently installed.)
Preparing to unpack .../google-drive-ocamlfuse_0.7.1-0ubuntu3~ubuntu18.04.1_amd64.deb ...
Unpacking google-drive-ocamlfuse (0.7.1-0ubuntu3~ubuntu18.04.1) ...
Setting up google-drive-ocamlfuse (0.7.1-0ubuntu3~ubuntu18.04.1) ...
Processing triggers for man-db (2.8.3-2ubuntu0.1) ...
Please, open the following URL in a web browser: https://accounts.google.com/o/oauth2/auth?client_id=[redacted].apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%3Ao
.........
Please, open the following URL in a web browser: https://accounts.google.com/o/oauth2/auth?client_id=[redacted].apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%3Ao
Please enter the verification code: Access token retrieved correctly.
done connecting to google drive
```

## Loading the model



```
[ ]  from sklearn.externals import joblib
     modelfile="drive/litemodel.sav"
     joblib.dump(random_forest,modelfile)

     ['drive/litemodel.sav']

     # load the model from drive
     loaded_model= joblib.load(modelfile)
     # result=loaded_model.score(X_test, y_test)
     # print(result)
     loaded_model
     print("loaded model")

     1.0
     loaded model
```

## Main.py Flask

```
from flask import Flask, render_template, request
import pandas as pd
import numpy as np
import urllib.request
import urllib.parse
import joblib

app = Flask(__name__)
model = joblib.load('litemodel.sav')

def sendSMS(apikey, numbers, sender, message):
    data = urllib.parse.urlencode({
        'apikey': apikey,
        'numbers': numbers,
        'message': message,
        'sender': sender
    })
    data = data.encode('utf-8')
    request_obj = urllib.request.Request("https://api.textlocal.in/send/?")
    f = urllib.request.urlopen(request_obj, data)
    fr = f.read()
    return fr

def cal(ip):
    input_data = dict(ip)
    Did_Police_Officer_Attend = input_data['Did_Police_Officer_Attend'][0]
    age_of_driver = input_data['age_of_driver'][0]
```

```
    vehicle_type = input_data['vehicle_type'][0]
    age_of_vehicle = input_data['age_of_vehicle'][0]
    engine_cc = input_data['engine_cc'][0]
    day = input_data['day'][0]
    weather = input_data['weather'][0]
    light = input_data['light'][0]
    roadsc = input_data['roadsc'][0]
    gender = input_data['gender'][0]
    speedl = input_data['speedl'][0]

    data = np.array([
        Did_Police_Officer_Attend, age_of_driver, vehicle_type, age_of_vehicle,
        engine_cc, day, weather, roadsc, light, gender, speedl
    ])

    print("Logging input:", data)
    data = data.astype(float).reshape(1, -1)

    try:
        result = model.predict(data)
    except Exception as e:
        result = str(e)
        return result

    return str(result[0])

@app.route('/', methods=['GET'])
def index():
    return render_template('index.html')

@app.route('/visual/', methods=['GET'])
def visual():
    return render_template('visual.html')

@app.route('/sms/', methods=['POST'])
def sms():
    res = cal(request.form)
    try:
        resp = sendSMS(
            'UwYs16dD3zM-DKuzZKQYolAJkoba1j0BmRGompsNRs',
            '9618205648',
            'TXTLCL',
            'Severe accident predicted!'
        )
        print(resp)
    except Exception as e:
```

```
        print("SMS Error:", e)
    return res

@app.route('/', methods=['POST'])
def get():
    return cal(request.form)

if __name__ == '__main__':
    app.run(host='0.0.0.0',debug=True,port=4000)
```

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