**CHAPTER – 1**

**INTRODUCTION**

**1.1 DOMAIN**

VoiceSignSpot.com is a pioneering platform at the intersection of sign board detection and voice recognition technologies. This innovative system aims to enhance accessibility and safety by providing users with real-time audio feedback on detected signs in their surroundings. By seamlessly integrating cutting-edge computer vision and natural language processing algorithms, VoiceSignSpot.com empowers individuals, including the visually impaired, drivers, and pedestrians, to navigate their environments more confidently. Users can easily access this service by registering on the website, where they can find comprehensive information about its features, benefits, and usage. Through strategic promotion via social media, forums, and targeted advertising, VoiceSignSpot.com endeavours to reach its intended audience and stakeholders, fostering greater inclusivity and convenience in everyday life.

**1.2 PROJECT NEEDS**

Project on Sign Board Detection Using Voice Recognition represents a groundbreaking fusion of computer vision and natural language processing technologies, aimed at revolutionizing accessibility and safety in navigation. By harnessing advanced algorithms, the system detects and interprets signs in real-time, translating them into spoken feedback for users. This innovation holds immense promise for diverse user groups, including the visually impaired, drivers, and pedestrians, offering them a seamless and intuitive means of understanding their surroundings. Through meticulous development and testing, the project endeavours to create a robust and reliable solution, empowering individuals to navigate with greater confidence and independence. With the potential to profoundly impact daily life, this project represents a significant step forward in leveraging technology for inclusivity and convenience. Additionally, robust connectivity infrastructure would facilitate seamless communication between the sign board, voice alert system, and central traffic management systems.

**1.3 FIELD**

Field of Sign Board Detection Using Voice Recognition represents a pioneering convergence of computer vision and natural language processing technologies, with the overarching goal of revolutionizing accessibility and safety in navigation. By leveraging sophisticated algorithms, this innovative field enables real-time detection and interpretation of signs, seamlessly translating them into spoken feedback for users. With applications spanning diverse user groups such as the visually impaired, drivers, and pedestrians, this field holds immense promise in providing intuitive and inclusive navigation solutions. Through rigorous research and development efforts, practitioners in this field aim to create robust and reliable systems, empowering individuals to navigate their environments with greater confidence and independence. As advancements continue to unfold, Sign Board Detection Using Voice Recognition stands poised to reshape the landscape of navigation technology, fostering inclusivity and convenience in everyday life.

**1.4 METHODS**

Various methods are employed in Sign Board Detection Using Voice Recognition to achieve accurate and efficient results. One prominent approach involves the integration of computer vision techniques for sign board detection, utilizing image processing algorithms to identify and extract signs from visual data. Concurrently, voice recognition technology is employed to interpret the extracted signs and convert them into spoken language. Machine learning algorithms play a crucial role in training models to recognize diverse sign board types and variations, enhancing system accuracy and adaptability. Additionally, natural language processing techniques are utilized to enable seamless communication between the system and users, ensuring effective interpretation and synthesis of spoken feedback. Through the synergistic integration of these methods, Sign Board Detection Using Voice Recognition aims to deliver robust and user-friendly navigation solutions for enhanced accessibility and safety. The system could incorporate GPS data to offer location-specific alerts and guidance, enhancing overall effectiveness and safety on the roads. This system would utilize natural language processing algorithms to generate appropriate verbal alerts, providing real-time guidance to drivers based on the detected traffic signs and road conditions.

**CHAPTER – 2**

**SYSTEM STUDY**

**INTRODUCTION**

In recent years, advancements in technology have spurred innovative solutions to enhance accessibility and safety in navigation for diverse user groups. One such pioneering endeavour is Sign Board Detection Using Voice Recognition, a cutting-edge system at the forefront of computer vision and natural language processing integration. This case study explores the development and implementation of this transformative technology, which aims to empower individuals, including the visually impaired, drivers, and pedestrians, with real-time sign board interpretation through spoken feedback. By harnessing sophisticated algorithms and machine learning techniques, this system promises to revolutionize the way users interact with their surroundings, offering seamless and intuitive navigation solutions. Through a comprehensive examination of its features, benefits, and real-world applications, this case study delves into the potential of Sign Board Detection Using Voice Recognition to reshape the landscape of navigation technology and foster greater inclusivity and convenience in everyday life. Introduction:

The Traffic Sign Board Detection and Voice Alert System heralds a new era in road safety technology, revolutionizing how drivers interact with and respond to traffic signs on the road. This innovative system combines advanced image processing algorithms with voice recognition technology to provide real-time detection and interpretation of traffic signs, delivering timely alerts to drivers through voice notifications. In an age where road safety is paramount, this system represents a crucial step towards mitigating accidents and promoting safer driving practices. By leveraging cutting-edge technologies, it empowers drivers with essential information about speed limits, stop signs, and other vital traffic regulations, enhancing their awareness and responsiveness while minimizing distractions. As road networks become increasingly complex and traffic conditions evolve, the Traffic Sign Board Detection and Voice Alert System emerges as a beacon of innovation, offering a comprehensive solution to enhance road safety and improve the overall driving experience for all road users.

**CHAPTER-3**

**SYSTEM ANALYSIS**

**3.1 EXISTING SYSTEM**

In analysing the existing system for Sign Board Detection Using Voice Recognition, several key components and functionalities emerge. The current system leverages computer vision algorithms to detect sign boards within visual data, employing image processing techniques to accurately identify and extract signage information. Simultaneously, voice recognition technology interprets the extracted signs and translates them into spoken language, enabling seamless communication with users. Machine learning algorithms play a pivotal role in enhancing system performance by continually refining sign board detection capabilities and adapting to diverse environmental conditions. Furthermore, the system undergoes rigorous testing and optimization to ensure reliability and accuracy in real-world scenarios. While the existing system represents a significant advancement in navigation technology, on-going research and development efforts are focused on further refining its capabilities to deliver even more robust and user-friendly solutions for enhanced accessibility and safety.

**3.2 DRAWBACKS IN EXISTING SYSTEM**

Despite its advancements, the existing system for Sign Board Detection Using Voice Recognition faces several drawbacks that warrant attention. One prominent limitation lies in its performance in complex and dynamic environments, where varying lighting conditions, occlusions, and sign board orientations can challenge accurate detection and interpretation. Additionally, the system may struggle with the recognition of non-standard or obscured signage, leading to potential inaccuracies in spoken feedback. Furthermore, there may be latency issues during the processing and translation of sign board information, resulting in delays in providing real-time feedback to users. Moreover, the current system may lack robustness in handling multilingual signage or dialectal variations, posing challenges for users in diverse linguistic contexts. Addressing these drawbacks through on-going research and development efforts is crucial to enhancing the reliability, adaptability, and user experience of Sign Board Detection Using Voice Recognition, ultimately advancing its potential to revolutionize navigation technology and promote greater inclusivity and accessibility for all users.

**3.3 PROPOSED SYSTEM**

Proposed system for Sign Board Detection Using Voice Recognition aims to address the limitations of the existing system while further advancing the capabilities and user experience. Building upon the foundation of computer vision and natural language processing, the proposed system integrates state-of-the-art deep learning algorithms to enhance sign board detection accuracy and robustness in various environmental conditions. By incorporating real-time feedback mechanisms and optimizing processing pipelines, the proposed system seeks to minimize latency and improve responsiveness, ensuring timely and accurate spoken feedback to users. Additionally, the system will undergo extensive training on diverse sign board types and linguistic variations, enabling seamless interpretation and synthesis of signage information across different languages and dialects. Furthermore, the proposed system will prioritize user-centric design principles, with a focus on accessibility features and intuitive interaction mechanisms to cater to the diverse needs of users, including the visually impaired, drivers, and pedestrians. Through these enhancements, the proposed system aims to set new benchmarks in navigation technology, fostering greater inclusivity, accessibility, and safety for all users in navigating their surroundings.

**3.4 PROBLEM DEFINITION**

Problem definition for Sign Board Detection Using Voice Recognition revolves around the need to create a robust and reliable system that addresses the challenges faced by various user groups, including the visually impaired, drivers, and pedestrians, in navigating their surroundings effectively. The primary challenge lies in developing a system capable of accurately detecting and interpreting sign boards in real-time, particularly in dynamic and complex environments characterized by varying lighting conditions, occlusions, and sign board orientations. Furthermore, the system must seamlessly integrate voice recognition technology to translate the detected sign board information into spoken feedback, ensuring accessibility and ease of use for users. Additionally, the system should be versatile enough to handle multilingual signage and dialectal variations, catering to users in diverse linguistic contexts. Overall, the problem definition underscores the need for an innovative and user-centric solution that leverages advanced technologies to enhance accessibility, safety, and independence in navigation for all users.

**3.5 OBJECTIVE OF PROPOSED SYSTEM**

Objective of the proposed system for Sign Board Detection Using Voice Recognition is to develop a cutting-edge solution that significantly enhances accessibility, safety, and user experience in navigation for diverse user groups. The primary goal is to create a robust and reliable system capable of accurately detecting and interpreting sign boards in real-time, regardless of environmental conditions or sign board variations. Through the seamless integration of computer vision and natural language processing technologies, the proposed system aims to provide users with timely and accurate spoken feedback on detected sign boards, facilitating intuitive navigation and decision-making. Additionally, the system will prioritize user-centric design principles, ensuring accessibility features and intuitive interaction mechanisms to cater to the specific needs of users, including the visually impaired, drivers, and pedestrians. Furthermore, the proposed system seeks to establish a scalable framework that can adapt to evolving technological advancements and user requirements, positioning it as a leading solution in the field of navigation technology. Overall, the objective is to empower individuals to navigate their surroundings with greater confidence, independence, and inclusivity, ultimately enhancing their quality of life.

**3.6 FEATURES OF PROPOSED SYSTEM**

* Enhanced Accessibility
* Efficient Sign Board Detection
* Voice-Based Interaction
* Real-Time Response
* Multi-Language Support
* Adaptability
* User-Friendly Interface
* Integration with Navigation Systems.
* Privacy and Security
* Scalability and Reliability

**CHAPTER - 4**

**SYSTEM SPECIFICATION**

**4.1 MINIMUM HARDWARE REQUIREMENTS**

Hardware refers to the computer’s tangible components or delivery systems that store and run the written instructions provided by the software. The software is the intangible part of the device that lets the user interact with the hardware and command it to perform specific tasks.

**Processor – i3 Intel**

A processor is an integrated electronic circuit that performs the calculations that run a computer. A processor performs arithmetical, logical, input/output (I/O) and other basic instructions that are passed form an operating system (OS). Most other processes are dependent on the operations of a processor. An Intel Corei3 is an Intel proprietary processor that is built on the framework of multiprocessor architecture. It is a type of dual-core processor with an integrated graphic processing unit (GPU).

**RAM – 4GB**

RAM (Random Access Memory) is the hardware in a computing device where the operating system (OS), application programs and data in current use are kept so they can be quickly reached by the device’s processor.

**HARD DISK – 128 GB**

Unformatted capacity is 128GB. The formatted, useful capacity will be maybe 5% less in real use due to the sectoring and directory information laid down in formatting.

**4.2 MINIMUM SOFTWARE REQUIREMENTS**

Software Requirements deal with defining software resource requirements and prerequisites that need to be installed on a computer to provide optimal functioning of an application. These requirements or pre-requisites are generally not included in the software installation package and need to be installed separately before the software is installed.

**OPERATING SYSTEM - WINDOWS 10**

An operating system (OS) is the program that, after being initially loaded into the computer by a boot program, manages all of the other application programs in a computer.

Software Requirements deal with defining software resource requirements and prerequisites that need to be installed on a computer to provide optimal functioning of an application. These requirements or pre-requisites are generally not included in the software installation package and need to be installed separately before the software is installed. The software requirements that are required for this project are:

* Panda
* Sklearn
* Pickel
* Tkinter

**4.3 INTEGRATED DEVELOPMENT ENVIRONMENT**

Development of the Car Price Prediction System necessitates a robust and versatile Integrated Development Environment (IDE) to enable efficient software engineering practices. An IDE serves as the digital workspace where programmers, data scientists, and developers collaborate to design, code, test, and refine the system. It provides a comprehensive suite of tools, features, and functionalities essential for streamlined software development. The chosen IDE for this project should offer robust code editing capabilities, enabling developers to write clean and efficient code. It should also provide seamless integration with data analysis and machine learning libraries, as data preprocessing and model training are integral components of the system. Additionally, version control and collaborative features are essential to facilitate teamwork among project contributors. Overall, the IDE plays a pivotal role in ensuring the successful development, testing, and deployment of the Car Price Prediction System.

**IDE PYCHARM**

PyCharm is an integrated development environment (IDE) used in computer programming, specifically for the Python programming language. It is developed by the Czech company JetBrains (formerly known as IntelliJ). It provides code analysis, a graphical debugger, an integrated unit tester, integration with version control systems (VCS’s).

**4.4 PACKAGES AND LIBRARIES**

A package is a collection of related modules that work together to provide certain functionality. These modules are contained within a folder and can be imported just like any other modules. This folder will often contain a package, potentially containing more modules nested within subfolders. A library is an umbrella term that loosely means “a bundle of code.” These can have tens or even hundreds of individual modules that can provide a wide range of functionality. Pandas is a file handling library. The Standard Library contains hundreds of modules for performing common tasks, like sending emails or reading JSON data. What’s special about the Standard Library is that it comes bundled with your installation of programming language, so you can use its modules without having to download them from anywhere.

**PANDAS**

Pandas is a Python library used for working with data sets. It has functions for analyzing, cleaning, exploring, and manipulating data. Pandas can clean messy data.

**SKLEARN**

Sklearn is a widely used open-source Python library for machine learning and data analysis. It provides a vast array of tools, algorithms, and functions for tasks related to machine learning, including classification, regression, clustering, dimensionality reduction, model selection, and data preprocessing.

**PICKLE**

Pickle is a Python module that provides a mechanism for serializing (pickling) and deserializing (unpickling) Python objects. Serialization is the process of converting Python objects into a byte stream, while deserialization is the process of reconstructing Python objects from that byte stream.

**TKINTER**

Tkinter is the standard Graphical User Interface (GUI) library for creating desktop applications in Python. It provides a set of Python modules for creating windows, dialogs, buttons, menus, and other GUI elements, making it a powerful and easy-to-use tool for developing desktop applications with graphical interfaces.

**DATASET**

Creating a dataset for Sign Board Detection Using Voice Recognition involves compiling a diverse collection of images containing various types of signboards commonly encountered in different environments, along with corresponding annotations indicating the location and content of each signboard. The dataset should encompass a wide range of signboard categories, such as street signs, directional signs, informational signs, and warning signs, in multiple languages and formats.

To ensure the effectiveness and robustness of the system, the dataset should include images captured under different lighting conditions, weather conditions, and angles, mimicking real-world scenarios. Additionally, variations in text font, size, colour, and background clutter should be represented to train the system to accurately detect and recognize signboards in challenging conditions.

Annotations within the dataset should provide detailed information about each signboard, including its textual content, language, position within the image, and any relevant metadata. Furthermore, audio recordings corresponding to the textual content of each signboard should be included to facilitate training of the voice recognition component.

It's crucial to adhere to ethical guidelines and privacy regulations when collecting and annotating the dataset, ensuring that any personal or sensitive information captured in the images is handled appropriately and anonymized if necessary. Collaborations with local authorities, transportation agencies, or commercial entities may be beneficial in acquiring a comprehensive and diverse dataset while respecting privacy concerns and legal requirements.

**CHAPTER - 5**

**SYSTEM DESIGN**

**5.1 INTRODUCTION**

In today's fast-paced world, accessing essential information while on the move is crucial for efficiency and safety. The integration of voice recognition technology with sign board detection presents an innovative solution to this challenge. Our proposed system aims to empower users by allowing them to interact with their surroundings through natural speech, enabling real-time identification and interpretation of sign boards. By leveraging advancements in artificial intelligence and computer vision, this system provides a seamless and intuitive way for individuals to access relevant information simply by vocalizing their queries. Whether navigating unfamiliar streets, searching for specific landmarks, or seeking essential directions, the fusion of voice recognition and sign board detection offers unparalleled convenience and accessibility. This system not only enhances user experience but also contributes to improved accessibility and inclusivity in urban environments. System Design Introduction:

The system design for the Traffic Sign Board Detection and Voice Alert System represents a meticulous integration of advanced technologies to address the critical need for enhanced road safety and driver awareness. Combining sophisticated image processing algorithms with voice recognition capabilities, the system aims to detect and interpret traffic signs in real-time, delivering timely alerts to drivers through voice notifications. The design process encompasses the development of robust algorithms for sign detection and classification, as well as the implementation of a user-friendly interface for seamless interaction.

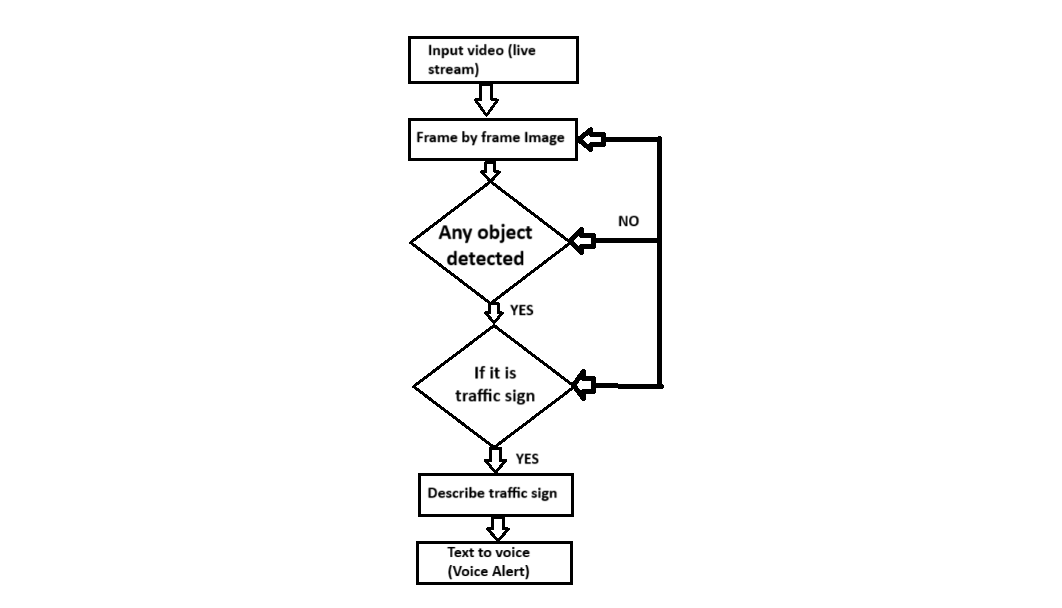
**5.2 DATAFLOW DIAGRAM**

Fig 1: Dataflow diagram

**5.3 SYSTEM ARCHITECTURE**

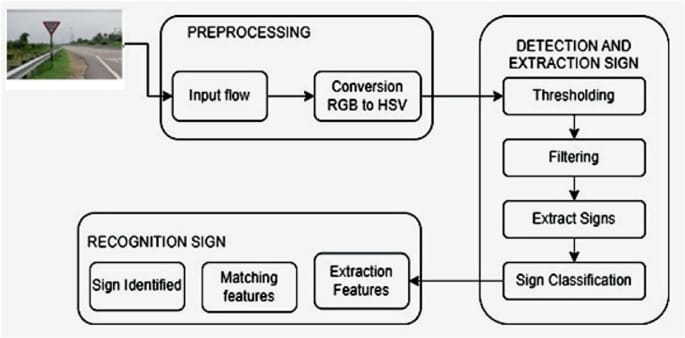


Fig 2: System Architecture

**5.4 DATA COLLECTION**

Collecting data for sign board detection using voice recognition involves gathering two main types of data: audio data for voice commands and image data for sign board detection.

For the audio data, a diverse range of voice commands and queries relevant to sign board information needs to be collected. This may include commands for requesting directions, identifying specific types of signs (e.g., street names, landmarks, facilities), and asking for additional information about detected signs. These voice commands should cover various accents, languages, and speech patterns to ensure robustness and accuracy of the voice recognition system. Additionally, contextual data such as GPS coordinates or timestamps can be recorded to enrich the dataset and improve the system's contextual understanding.

On the other hand, image data needs to be collected to train the sign board detection model. This involves capturing images containing different types of sign boards in various environments, lighting conditions, and orientations. It's essential to include a wide variety of sign boards, such as traffic signs, street signs, business signs, and informational signs, to ensure the model's versatility and generalization ability. Ground truth annotations, indicating the location and type of each sign board in the images, should be generated to facilitate supervised learning.

Furthermore, to enhance the performance of the system, it may be beneficial to collect additional data related to sign board attributes, such as text content, colours, shapes, and symbols. This supplementary data can be used to enrich the sign board detection model and improve its accuracy in identifying and extracting relevant information from detected signs.

In summary, data collection for sign board detection using voice recognition involves gathering a comprehensive dataset of audio commands, images containing various types of sign boards, and associated annotations. This data serves as the foundation for training and optimizing the voice recognition and sign board detection components of the system, ultimately enabling accurate and reliable performance in real-world scenarios.

**5.5 DATA PRE-PROCESSING**

The Data Preprocessing module serves as a crucial initial step in the car price prediction system, responsible for refining the raw data before it undergoes analysis and model training. Its primary objective is to enhance data quality by effectively addressing common data quality issues encountered in real-world datasets. One of the fundamental tasks undertaken by this module is the handling of missing values within the dataset. These missing entries can significantly impact the accuracy and reliability of predictive models. This may involve data imputation, where missing values are replaced or estimated using statistical techniques, or, in cases of excessive missingness, the elimination of corresponding records to ensure the dataset's integrity. Another critical aspect addressed by the Data Preprocessing module is the identification and removal of duplicate entries. Duplicate records can introduce bias into the analysis and model training processes. Therefore, a thorough examination of the dataset is conducted to identify and eliminate any redundant data points.

**5.6 FEATURE IDENTIFICATION**

The Feature Identification module plays a pivotal role in optimizing the predictive modelling process by identifying and selecting the most influential attributes or features from the dataset. This step is essential for improving the efficiency and accuracy of the car price prediction system. To begin, domain knowledge is leveraged to gain a comprehensive understanding of the factors that significantly impact car prices. Attributes like car make, model, year, and mileage are often deemed crucial, as they reflect inherent characteristics of the vehicle that buyers commonly consider when making purchasing decisions. In addition to domain knowledge, data exploration techniques are employed to validate and refine the selection of features. Exploratory data analysis (EDA) involves visualizing and summarizing data patterns, which aids in identifying correlations and dependencies between features and the target variable—car prices.

**5.7 ENCODING AND TRANSFORMATION**

The Encoding and Transformation module plays a crucial role in the data preparation pipeline for machine learning. One of its primary tasks is handling categorical features, which are attributes that do not have a natural numerical representation. In the context of car price prediction, categorical features can include car make, model, fuel type, and transmission type. To make these categorical features compatible with machine learning algorithms, encoding techniques are applied. One common approach is one-hot encoding, where each category within a feature is transformed into a binary column. This binary representation preserves the categorical information while enabling models to work with it effectively. For instance, a "car make" feature with categories like "Toyota," "Honda," and "Ford" would be transformed into separate binary columns, each indicating the presence or absence of a specific make. Another aspect of the Encoding and Transformation module is numerical feature scaling. It addresses the issue of varying feature scales within the dataset. In some cases, certain numerical features may have significantly larger ranges or magnitudes than others. By executing both encoding and scaling operations, the module prepares the dataset in a format that machine learning algorithms can readily consume. This transformation ensures that the data's inherent information is preserved while eliminating compatibility issues that could hinder the model's ability to generalize from the data effectively. In essence, the Encoding and Transformation module acts as a bridge, facilitating seamless communication between the dataset's characteristics and the machine learning models tasked with predicting car prices.

**5.8 DATA SPLITTING**

The Data Splitting module is a fundamental component of the machine learning workflow, responsible for partitioning the dataset into distinct subsets with specific roles. Its primary purpose is to establish a clear division between data used for model training and data used for model evaluation. This separation is critical because it simulates the real-world scenario where a trained model needs to make predictions on new, previously unseen data. The first subset, known as the training set, is the portion of the data that the machine learning model learns from. It contains historical information about car attributes and their corresponding prices. During the training phase, the model identifies patterns, relationships, and correlations within this data. The goal is for the model to capture the underlying trends in car prices based on features like make, model year, mileage, and more. By learning from the training set, the model aims to generalize its knowledge to make accurate predictions on new car data.

The second subset, referred to as the testing set, is distinct from the training data. It serves as an independent benchmark to assess the model's performance. The testing set contains examples of cars with attributes similar to those in the training set but with withheld price information. The model's task is to predict the prices of these test cars based on the patterns it learned during training. By comparing its predictions to the actual prices in the testing set, the model's accuracy and generalization ability are evaluated. This evaluation step ensures that the model can make reliable predictions on cars it has never encountered before, demonstrating its real-world applicability. Proper data splitting and the clear distinction between training and testing data are essential to building trustworthy and effective machine learning models for car price prediction.

**5.9 MODEL SELECTION AND TRAINING**

The Model Selection and Training module are pivotal in the car price prediction system, as it determines the predictive power and accuracy of the machine learning model. The first step, model selection, involves a careful assessment of various regression algorithms to determine the most suitable one for the task at hand. This decision hinges on several factors, including the nature of the dataset, the complexity of price prediction, and the interpretability of the chosen algorithm. For instance, linear regression is a straightforward choice when there's a linear relationship between car attributes and prices, while random forest regression may be favored for capturing complex nonlinear patterns. Once the appropriate regression model is chosen, the training process begins. This phase exposes the selected model to the training dataset, where it learns the underlying patterns and associations between car attributes and prices. Through iterative optimization and adjustment of model parameters, such as weights and biases, the model fine-tunes its predictive capabilities. Techniques like cross-validation are often employed to ensure that the model generalizes well to unseen data and is not overfitting to the training dataset. By the end of this module, the machine learning model becomes a knowledgeable predictor, capable of making informed and accurate predictions of car prices based on the input features.

**5.10 USER INTERFACE**

The User Interface module is the gateway for users to interact with your car price prediction system. It involves the development of a user-friendly interface that allows users to input car details conveniently and receive price predictions seamlessly. This module may encompass various technologies, such as web development frameworks, mobile app development, or command-line interfaces, depending on your project's target audience and requirements. The interface acts as a bridge between users and the predictive model, facilitating user inputs and presenting the model's predictions in an understandable and accessible format. A well-designed user interface enhances the overall usability and accessibility of your system, making it user-friendly and efficient for users to obtain price predictions for cars based on their specifications. User Interface Introduction:

The user interface for the Traffic Sign Board Detection and Voice Alert System is designed with simplicity, intuitiveness, and efficiency in mind, aiming to provide drivers with a seamless and informative interaction experience. Featuring a clean and visually appealing layout, the interface presents real-time detection of traffic signs captured by the device's camera, accompanied by clear and concise voice alerts to convey essential information to the driver. Through intuitive controls and minimalistic design elements, users can easily access additional features such as settings customization, voice alert preferences, and historical sign detection logs. The interface prioritizes usability and accessibility, ensuring that drivers can effortlessly engage with the system while maintaining their focus on the road ahead, ultimately contributing to safer driving practices and enhanced road safety for all.

**CHAPTER – 6**

**SYSTEM TESTING**

**6.1 INTRODUCTION**

Testing serves a fundamental purpose in the development and quality assurance of software and systems. Its overarching goal is to identify and rectify errors, faults, or weaknesses present in a work product. By systematically examining a software application or system, testing seeks to uncover any conceivable issues that might impede its functionality or reliability. This process extends to evaluating the components, sub-assemblies, assemblies, and the final product to ensure it meets predefined standards and specifications. Ultimately, testing is the means through which software systems are exercised to verify that they align with their intended purpose, fulfil user expectations, and operate without unacceptable failures. The testing landscape encompasses various types, each tailored to address specific testing requirements and objectives. These test types include unit testing, integration testing, system testing, acceptance testing, regression testing, and more. Each type has a defined scope and focus, ranging from scrutinizing the behavior of individual software units to assessing the overall system's functionality, performance, and user experience. Through this diversity of test types, the testing process aims to comprehensively validate the software's correctness, robustness, and suitability for its intended use.

* Testing the basic logic of the model.
* Managing the model performance by using manual testing.
* Evaluating the accuracy of the ML model.
* Make sure that the achieved loss is acceptable for your task.
* Checking model performance on real data.

**6.2 TYPES OF TESTING**

Fig 3: Types of testing

**6.3 UNIT TESTING**

Unit testing is a foundational aspect of the testing process, focusing on the smallest, independently testable components within your car price prediction system. These components are typically individual functions or methods that carry out specific tasks within the system's architecture. In the context of your car price prediction system, unit testing would involve subjecting functions responsible for critical operations, such as data preprocessing, model training, and data encoding, to rigorous testing. The primary objective is to confirm that each of these components functions correctly in isolation, irrespective of the entire system's complexity.

One of the primary advantages of unit testing is its ability to detect and rectify errors and issues at an early stage in the development process. By isolating specific components and rigorously testing them, developers can identify and address problems before they have the chance to propagate to other interconnected parts of the system. This early error detection significantly reduces the complexity of debugging and maintaining the system, ultimately leading to a more robust and reliable car price prediction system. For example, consider the data preprocessing function within your system. Unit testing for this function would entail evaluating its ability to handle missing data accurately. Does it impute missing values effectively, or does it remove them appropriately based on predefined criteria? Similarly, when unit testing the model training function, the focus would be on ensuring that the training process converges as expected, and the resulting model captures the underlying patterns in the data.

**6.4 INTEGRATION TESTING**

Integration testing is a pivotal phase in the testing process, particularly for a complex system like your car price prediction system. Its primary objective is to evaluate how different components, modules, or subsystems of the system interact and collaborate when integrated into a cohesive whole. In the context of your system, integration testing plays a crucial role in ensuring that all the integral parts, from the user interface to the predictive model, communicate and work harmoniously together.One key aspect of integration testing within your system is to assess the communication channels between various modules. For instance, when a user interacts with the system's interface by inputting car details, integration testing ensures that this input is correctly and efficiently transmitted to the predictive model. It examines whether the data flow mechanisms effectively pass user inputs to the model for analysis and price prediction. Similarly, integration testing validates that the model's predictions seamlessly integrate back into the interface, ensuring that users receive accurate and timely price estimates.

By conducting integration testing, you can identify and address any potential issues related to data flow, communication protocols, or module interactions. This proactive approach helps uncover problems that might arise when different parts of the system work together. Addressing these issues during integration testing is essential to ensure the smooth and reliable functioning of your car price prediction system as a unified whole. Ultimately, integration testing contributes to the system's overall stability and user experience by verifying that all its components collaborate to deliver accurate price predictions.

**6.5 REGRESSION TESTING**

Regression testing is a critical aspect of maintaining the reliability and stability of your car price prediction system, especially as it evolves over time. This testing process ensures that any changes, enhancements, or updates made to the system do not introduce new issues or compromise the functionality of existing components. In essence, regression testing acts as a safety net, guarding against unintended consequences that can arise when modifying the system.In the context of your system, regression testing becomes particularly important when you make alterations to key components such as the machine learning model or the user interface. When updating the machine learning model, for example, regression testing verifies that the new model performs at least as well as the previous one and that it continues to provide accurate price predictions. Additionally, it ensures that any modifications to the user interface, which serves as the bridge between users and the model, do not hinder the user experience or disrupt the seamless flow of data and information.

By conducting regression tests after each update, you can systematically confirm that the system's core functionalities remain intact and that any changes introduced do not lead to unexpected issues. This proactive approach not only helps in maintaining the system's integrity but also instills confidence in its performance, assuring users that updates are thoroughly tested and validated. Ultimately, regression testing contributes to the ongoing success and reliability of your car price prediction system in the dynamic automotive industry.

**6.6 PERFORMANCE TESTING**

Performance testing is a critical phase in ensuring that your car price prediction system not only delivers accurate predictions but also does so efficiently and reliably. It goes beyond evaluating the correctness of the predictions and focuses on assessing the system's ability to handle various workloads and user demands effectively.This aspect gauges how quickly the system responds to user inputs and requests for price predictions. It ensures that users receive timely feedback and results, enhancing their overall experience. For your system, responsiveness testing might involve measuring the time it takes for the user interface to display predictions after receiving input data. Scalability testing assesses how well your system can adapt to increasing loads and user demands. It helps identify performance bottlenecks and constraints that could limit the system's ability to serve a growing user base.

By conducting comprehensive performance testing, you can fine-tune your car price prediction system to deliver a seamless and efficient user experience, regardless of the workload. This proactive approach helps identify and mitigate performance-related issues, ensuring that the system remains responsive, scalable, and resource-efficient as it serves users in the dynamic automotive market.

**CHAPTER – 7**

**SYSTEM IMPLEMENTATION**

**7.1 RANDOM FOREST REGRESSION**

Random Forest Regression is a powerful and versatile machine learning algorithm used for both regression and classification tasks. It is a robust and widely adopted algorithm for various applications, including car price prediction. It belongs to the ensemble learning family of algorithms, which combine the predictions of multiple machine learning models to improve accuracy and reduce overfitting. Random Forest Regression is particularly well-suited for predicting numerical or continuous values, making it an excellent choice for tasks like car price prediction.

**7.1.1 Ensemble Learning**

Random Forest Regression is a prominent ensemble learning algorithm used extensively for regression tasks. The essence of ensemble learning lies in combining multiple machine learning models to enhance predictive accuracy and mitigate overfitting. In the case of Random Forest Regression, it creates a "forest" of decision trees during training. By aggregating predictions from these individual trees, it generates a more robust and accurate prediction.

**7.1.2 DECISION TREES IN THE FOREST**

Core building blocks of Random Forest are decision trees. Each tree in the forest is constructed using a random subset of the training data and a random subset of the available features (also known as feature bagging or random feature selection). This inherent randomness introduces diversity into the ensemble, which helps combat overfitting and improve generalization. By aggregating predictions across these diverse trees, the algorithm produces a collective output that is often more stable and less prone to errors.

**7.1.3 REDUCTION OF OVERFITTING**

Overfitting occurs when a model learns to perform well on the training data but fails to generalize to unseen data. Random Forest mitigates overfitting by introducing randomness in the model-building process. By using random subsets of features and data samples for each tree, it reduces the risk of individual trees memorizing the training data.

**7.1.4 FEATURE IMPORTANCE**

Random Forest provides a measure of feature importance, indicating which attributes have the most significant impact on predictions. This information can be valuable for understanding the factors influencing car prices and for feature selection in your model.

**7.1.5 PREDICTIVE POWER**

Random Forest Regression's predictive prowess extends to handling noisy data and mitigating overfitting. In the context of car price prediction, it can gracefully manage outliers and missing values, common challenges when dealing with used car data. This robustness ensures that the model's predictions remain reliable even when the dataset exhibits imperfections. Another advantage lies in its ability to provide insights into feature importance. Random Forest assigns importance scores to each input feature, indicating their contribution to the prediction.

**7.1.6 NON-LINEARITY HANDLING**

Ability to model non-linear relationships is a significant advantage of Random Forest Regression. When predicting car prices, linear models may fall short because factors like mileage, age, and specific car features often exhibit non-linear effects on price. Random Forest Regression excels in capturing these non-linearities, enabling it to provide more accurate predictions.

**CHAPTER – 8**

**CONCLUSION**

The integration of a Traffic Sign Board Detection and Voice Alert System signifies a pivotal advancement in road safety technology, offering a comprehensive solution to enhance driver awareness and mitigate potential hazards on the road. Through sophisticated image processing algorithms and leveraging artificial intelligence and machine learning, this system adeptly identifies and interprets traffic signs in real-time across various environmental conditions and road scenarios, providing timely and clear voice notifications to drivers. By actively assisting drivers in maintaining vigilance and compliance with traffic regulations, it reduces the likelihood of accidents and traffic violations. Moreover, the implementation of voice alerts minimizes distraction and cognitive load on drivers, allowing them to focus more on the road ahead while staying informed about critical information conveyed by traffic signs. Its adaptability and scalability ensure ongoing relevance and effectiveness, future-proofing the technology and positioning it as a vital component of modern road safety initiatives. Furthermore, by fostering a culture of responsible driving and shared road safety responsibility, it encourages proactive decision-making and risk mitigation strategies, ultimately leading to safer road environments for all road users. In conclusion, the integration of a Traffic Sign Board Detection and Voice Alert System represents a significant leap forward in road safety technology, paving the way for safer and more efficient road networks while saving lives and improving the quality of our urban environments.

**CHAPTER – 9**

**FUTURE ENHANCEMENT**

**9.1 Real-time Market Insights:**

Real-time market insights for sign board detection using voice recognition offer a glimpse into the evolving landscape of urban navigation and accessibility solutions. As urbanization accelerates and the demand for seamless, user-friendly experiences grows, the integration of voice recognition technology with sign board detection stands at the forefront of innovation. Real-time data analysis provides invaluable market intelligence, revealing trends in user preferences, emerging use cases, and technological advancements. By tracking user interactions, feedback, and adoption rates, businesses and developers can identify opportunities for optimization and customization, ensuring that the system meets the diverse needs of its users. Moreover, monitoring competitor offerings and market dynamics enables stakeholders to stay agile and responsive, swiftly adapting their strategies to capitalize on emerging opportunities or address potential challenges. As the market for sign board detection using voice recognition continues to evolve, real-time insights serve as a compass, guiding stakeholders toward informed decision-making and sustainable growth in this dynamic landscape.

**9.2 Image Recognition Integration:**

The integration of image recognition technology plays a pivotal role in enhancing the efficacy and versatility of sign board detection using voice recognition. By seamlessly incorporating image recognition capabilities into the system, users can benefit from a comprehensive and intuitive experience that combines both auditory and visual cues. Image recognition enables the system to accurately identify and analyze sign boards captured in real-time through cameras or images provided by users. Leveraging advanced computer vision techniques such as convolutional neural networks (CNNs), the system can detect various types of sign boards, including street signs, traffic signals, and informational boards, with high accuracy and efficiency. This integration not only enhances the system's ability to interpret user queries accurately but also enables it to provide contextual information and visual feedback, further enriching the user experience. Additionally, by continuously refining its image recognition algorithms through machine learning and data-driven optimization, the system can adapt to diverse environments, lighting conditions, and signage variations, ensuring robust performance in real-world scenarios. In essence, the seamless integration of image recognition technology into sign board detection using voice recognition transforms the user interface into a dynamic and multifaceted tool for urban navigation and accessibility.

**9.3 Mobile Application Development:**

Mobile Application Development for Traffic Sign Board Detection and Voice Alert System presents a cutting-edge solution to enhance road safety and driver awareness through the integration of advanced technologies into everyday devices. By leveraging the power of mobile platforms, this application provides users with a user-friendly interface to access real-time traffic sign detection and voice alerts directly on their smartphones or tablets. Through sophisticated image processing algorithms and machine learning techniques, the application swiftly identifies and interprets traffic signs captured by the device's camera, delivering timely voice notifications to users to alert them about crucial information such as speed limits, stop signs, or hazardous road conditions. The development of this mobile application not only empowers drivers with valuable information but also promotes safer driving habits by minimizing distractions and cognitive load through voice alerts. Moreover, the portability and accessibility of the application enable users to benefit from enhanced road safety features wherever they go, contributing to creating safer transportation ecosystems. Overall, Mobile Application Development for Traffic Sign Board Detection and Voice Alert System represents a significant step forward in leveraging mobile technology to improve road safety and enhance the driving experience for all road users.

**APPENDIX**

**10.1 SOURCE CODE**

**Traffic\_sign\_train.py**

import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import tensorflow as tf

from PIL import Image

import os

from sklearn.model\_selection import train\_test\_split

from keras.utils import to\_categorical

from keras.models import Sequential

from keras.layers import Conv2D, MaxPool2D, Dense, Flatten, Dropout

data = []

labels = []

classes = 43

cur\_path = os.getcwd()

for i in range(classes):

path = os. path.join(cur\_path,'train', str(i))

images = os.listdir(path)

for a in images:

try:

image = Image.open(path + '/' + a)

image = image.resize((30,30))

image = np.array(image)

data.append(image)

labels.append(i)

except:

print("Error loading image")

data = np.array(data)

labels = np.array(labels)

print(data.shape, labels.shape)

#Splitting training and testing dataset

X\_t1, X\_t2, y\_t1, y\_t2 = train\_test\_split(data, labels, test\_size=0.2, random\_state=42)

print(X\_t1.shape, X\_t2.shape, y\_t1.shape, y\_t2.shape)

#Converting the labels into one hot encoding

y\_t1 = to\_categorical(y\_t1, 43)

y\_t2 = to\_categorical(y\_t2, 43)

#CNN building the model

model = Sequential()

model.add(Conv2D(filters=32, kernel\_size=(5,5), activation='relu', input\_shape=X\_t1.shape[1:]))

model.add(Conv2D(filters=32, kernel\_size=(5,5), activation='relu'))

model.add(MaxPool2D(pool\_size=(2, 2)))

model.add(Dropout(rate=0.25))

model.add(Conv2D(filters=64, kernel\_size=(3, 3), activation='relu'))

model.add(Conv2D(filters=64, kernel\_size=(3, 3), activation='relu'))

model.add(MaxPool2D(pool\_size=(2, 2)))

model.add(Dropout(rate=0.25))

model.add(Flatten())

model.add(Dense(256, activation='relu'))

model.add(Dropout(rate=0.5))

model.add(Dense(43, activation='softmax'))

#Compilation of the model

model.compile(loss='categorical\_crossentropy', optimizer='adam', metrics=['accuracy'])

#traing the model

history= model.fit(X\_t1, y\_t1, batch\_size=32, epochs=10, validation\_data=(X\_t2, y\_t2))

model.save("my\_model.h5")

#plotting graphs for accuracy

plt.figure(0)

plt.plot(history.history['accuracy'], label='training accuracy')

plt.plot(history.history['val\_accuracy'], label='val accuracy')

plt.title('Accuracy')

plt.xlabel('epochs')

plt.ylabel('accuracy')

plt.legend()

plt.show()

plt.figure(1)

plt.plot(history.history['loss'], label='training loss')

plt.plot(history.history['val\_loss'], label='val loss')

plt.title('Loss')

plt.xlabel('epochs')

plt.ylabel('loss')

plt.legend()

plt.show()

from sklearn.metrics import accuracy\_score

y\_test = pd.read\_csv('Test.csv')

labels = y\_test["ClassId"].values

imgs = y\_test["Path"].values

data=[]

for img in imgs:

image = Image.open(img)

image = image.resize((30,30))

data.append(np.array(image))

X\_test=np.array(data)

#pred = model.predict(X\_test)

predictions = model.predict(X\_test)

pred=np.argmax(predictions, axis=-1)

#Accuracy with the test data

from sklearn.metrics import accuracy\_score

print(accuracy\_score(labels, pred))

model.save('traffic\_classifier.h5')

**Live\_Cam.py**

import cv2

import numpy as np

import pyttsx3

from tensorflow.keras.models import load\_model # Assuming TensorFlow for model loading

# Replace placeholders with your actual model and labels

model\_path = ("traffic\_classifier.h5") #(HDF5 or other format)

labels\_path =("labels.csv") # One label per line

# Load pre-trained traffic sign classification model (adapt to your model format)

model = load\_model(model\_path)

# Load traffic sign labels

with open(labels\_path, 'r') as f:

labels = f.read().strip().split("\n")

# Function for image preprocessing (adaptable to different algorithms)

def preprocess\_image(image):

# Resize image to expected input size (check model requirements)

image = cv2.resize(image, (30, 30)) # Example size, adjust for your model

# Convert image to BGR (OpenCV format) if needed

image = cv2.cvtColor(image, cv2.COLOR\_RGB2BGR)

# Normalize pixel values (typical range: 0-1 or -1 to 1)

image = image.astype(np.float32) / 255.0

# (Optional) Apply other preprocessing steps as needed by your model

# Prepare image for model input

image = np.expand\_dims(image, axis=0) # Add batch dimension (if model expects it)

return image

# Initialize text-to-speech engine

engine = pyttsx3.init()

voices = engine.getProperty('voices') # Get available voices (optional)

engine.setProperty('voice', voices[0].id) # Set default voice (optional)

# Start video capture (replace with your video source)

cap = cv2.VideoCapture(0) # Use 0 for webcam, path to video file otherwise

while True:

# Capture frame-by-frame

ret, frame = cap.read()

# Preprocess frame

preprocessed\_image = preprocess\_image(frame)

#print(preprocessed\_image.shape)

# Assuming preprocessed\_image is a 1D array

#original\_shape = preprocessed\_image.shape

#print("Original shape:", original\_shape)

#flattened\_data = preprocessed\_image.reshape((preprocessed\_image.shape[0], -1)) # Flatten all dimensions except the first (batch size)

#predictions = model.predict(flattened\_data)

reshaped\_data =preprocessed\_image.reshape((preprocessed\_image.shape[0], 30, 30, 3)) # Reshape to (batch\_size, height, width, channels)

predictions = model.predict(reshaped\_data)

# Make prediction using the model

#predictions = model.predict(preprocessed\_image)

# Get the index of the most confident prediction

predicted\_class\_idx = np.argmax(predictions[0])

predicted\_class = labels[predicted\_class\_idx]

confidence = predictions[0][predicted\_class\_idx]

# Display prediction (optional)

cv2.putText(frame, f"Sign: {predicted\_class} (Conf: {confidence:.2f})",

(10, 20), cv2.FONT\_HERSHEY\_SIMPLEX, 0.7, (0, 255, 0), 2)

# Generate voice alert (consider thresholding for confidence)

if confidence > 0.7: # Adjust threshold as needed

engine.say(f"Traffic sign detected: {predicted\_class}")

engine.runAndWait()

# Display the resulting frame

cv2.imshow('Traffic Sign Detection', frame)

# Exit loop on 'q' key press

if cv2.waitKey(1) & 0xFF == ord('q'):

break

# Release capture and clean up

cap.release()

cv2.destroyAllWindows()

engine.stop()

engine.shutdown()

**gui.py**

import tkinter as tk

from tkinter import filedialog

from tkinter import \*

from PIL import ImageTk, Image

import numpy

#load the trained model to classify sign

from keras.models import load\_model

model = load\_model('traffic\_classifier.h5')

#dictionary to label all traffic signs class.

classes = { 1:'Speed limit (20km/h)',

2:'Speed limit (30km/h)',

3:'Speed limit (50km/h)',

4:'Speed limit (60km/h)',

5:'Speed limit (70km/h)',

6:'Speed limit (80km/h)',

7:'End of speed limit (80km/h)',

8:'Speed limit (100km/h)',

9:'Speed limit (120km/h)',

10:'No passing',

11:'No passing veh over 3.5 tons',

12:'Right-of-way at intersection',

13:'Priority road',

14:'Yield',

15:'Stop',

16:'No vehicles',

17:'Veh > 3.5 tons prohibited',

18:'No entry',

19:'General caution',

20:'Dangerous curve left',

21:'Dangerous curve right',

22:'Double curve',

23:'Bumpy road',

24:'Slippery road',

25:'Road narrows on the right',

26:'Road work',

27:'Traffic signals',

28:'Pedestrians',

29:'Children crossing',

30:'Bicycles crossing',

31:'Beware of ice/snow',

32:'Wild animals crossing',

33:'End speed + passing limits',

34:'Turn right ahead',

35:'Turn left ahead',

36:'Ahead only',

37:'Go straight or right',

38:'Go straight or left',

39:'Keep right',

40:'Keep left',

41:'Roundabout mandatory',

42:'End of no passing',

43:'End no passing veh > 3.5 tons' }

#initialise GUI

top=tk.Tk()

top.geometry('800x600')

top.title('Traffic sign classification')

top.configure(background='#CDCDCD')

label=Label(top,background='#CDCDCD', font=('arial',15,'bold'))

sign\_image = Label(top)

def classify(file\_path):

global label\_packed

image = Image.open(file\_path)

image = image.resize((30,30))

image = numpy.expand\_dims(image, axis=0)

image = numpy.array(image)

print(image.shape)

#pred = model.predict\_classes([image])[0]

pred = numpy.argmax(model.predict([image])[0])

sign = classes[pred+1]

print(sign)

label.configure(foreground='#011638', text=sign)

def show\_classify\_button(file\_path):

classify\_b=Button(top,text="ClassiImage",command=lambda: classify(file\_path),padx=10,pady=5)

classify\_b.configure(background='#364156', foreground='white',font=('arial',10,'bold'))

classify\_b.place(relx=0.79,rely=0.46)

def upload\_image():

try:

file\_path=filedialog.askopenfilename()

uploaded=Image.open(file\_path)

uploaded.thumbnail(((top.winfo\_width()/2.25),(top.winfo\_height()/2.25)))

im=ImageTk.PhotoImage(uploaded)

sign\_image.configure(image=im)

sign\_image.image=im

label.configure(text='')

show\_classify\_button(file\_path)

except:

pass

upload=Button(top,text="Upload animage",command=upload\_image,padx=10,pady=5)

upload.configure(background='#364156', foreground='white',font=('arial',10,'bold'))

upload.pack(side=BOTTOM,pady=50)

sign\_image.pack(side=BOTTOM,expand=True)

label.pack(side=BOTTOM,expand=True)

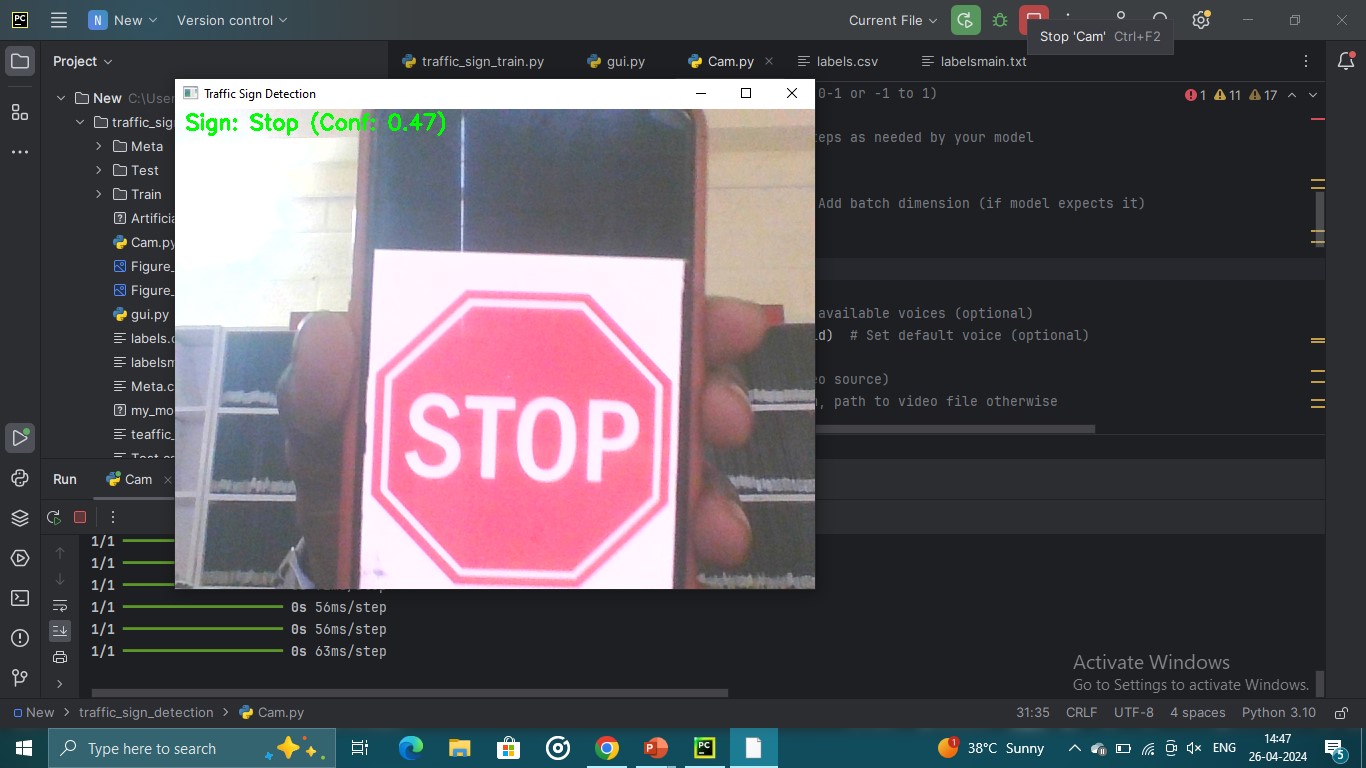
heading = Label(top, text="Know Your Traffic Sign",pady=20, font=('arial',20,'bold'))

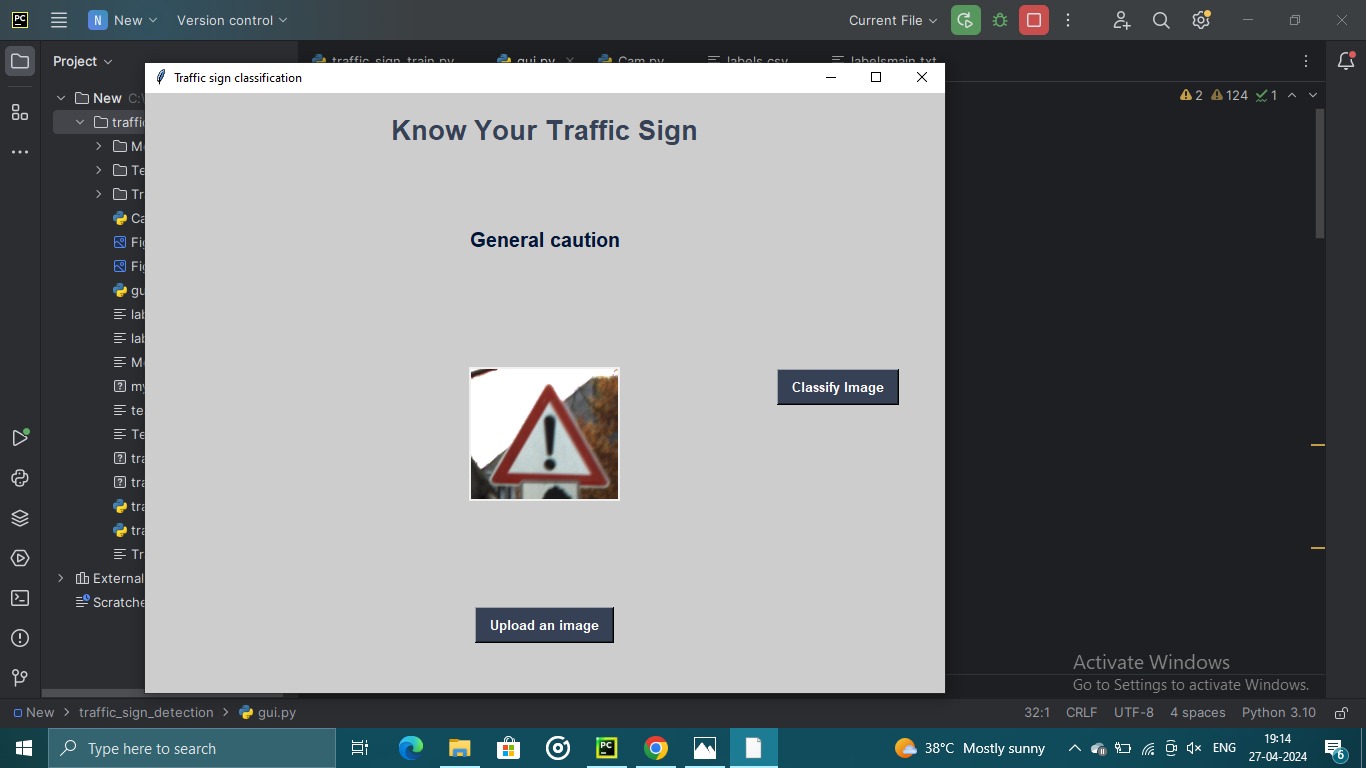
heading.configure(background='#CDCDCD',foreground='#364156')

heading.pack()

top.mainloop()

10.2 SCREENSHOT





Top of Form

**Reference:**

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