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INTELLIGENT TRANSPORTATION SYSTEM FOR TRAFFIC FORECASTING USING YOLO AND ENSEMBLE LEARNING TECHNIQUES

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Abstract –
Traffic management is a critical aspect of urban infrastructure, impacting not only the efficiency of transportation but also the quality of life for residents. The study aims to develop a smart system that can use YOLO to "see" and comprehend traffic circumstances. It then uses ensemble learning techniques to generate accurate forecasts of the behavior of traffic in the near future. Initially, various image-based detection models including YOLOv5, v6, v7, and v8 are implemented to classify traffic into high, moderate, and low density. Subsequently, data-based prediction models such as Support Vector Machines (SVM), AdaBoost, XGBoost, and a Voting Classifier are utilized to predict traffic flow. The base paper reported SVM achieving 65% accuracy, while propose method, achieved 92% accuracy, showcasing significant improvement. This integrated approach promises to revolutionize traffic management systems by providing accurate predictions and real-time detection, ultimately optimizing traffic flow and ensuring safer journeys.

Keywords:-
Traffic prediction, Deep learning, Machine learning, YOLO (You Only Look Once), Support Vector Machines (SVM), Ada Boost, XG Boost, Voting Classifier, Real-time traffic detection, Flask framework.

I. INTRODUCTION

The management and infrastructure of the transportationhave faced major issues due to the fast urbanization and rise in vehicle traffic in metropolitan regions. Leveraging cutting-edge technology like machine learning and deep learning is becoming more and more important in order to address these issues and boost the effectiveness of traffic management systems. This study presents a novel method for traffic forecasting called "Intelligent Transportation System for Traffic Forecasting Using YOLO and Ensemble Learning Techniques." To precisely predict traffic flow, the system combines ensemble learning techniques with the real-time traffic detection YOLO (You Only Look Once) algorithm. Combining these state-of-the-art methods, the system seeks to transform traffic management by offering accurate and timely insights into traffic patterns, facilitating proactive actions to reduce congestion, improve safety, and maximize the effectiveness of transportation as a whole.
Traffic management is a critical aspect of urban infrastructure, impacting not only the efficiency of transportation but also the quality of life for residents. As cities continue to grow, the need for effective traffic management systems becomes increasingly pressing. In response to this challenge, researchers have been exploring innovative approaches and technologies to optimize traffic flow, enhance safety, and reduce congestion.

One avenue of research focuses on developing smart traffic management systems, which integrate various technologies and algorithms to monitor, analyze, and control traffic patterns in real-time. These systems utilize advanced computational methods, such as machine learning and artificial intelligence, to predict short-term traffic flow and optimize traffic control strategies [1]. For instance, neural network-based models have shown promising results in short-term traffic flow forecasting, combining techniques like exponential smoothing and the Levenberg–Marquardt algorithm [2].

Moreover, the advent of TinyML (Machine Learning on microcontrollers) has enabled the deployment of adaptive traffic control systems capable of real-time decision-making at the edge [3]. Additionally, advancements in computer vision have facilitated the development of sophisticated road traffic monitoring systems, such as improved YOLO-based models for accurate object detection and tracking [4].

Furthermore, research efforts have been directed towards optimizing traffic light timings using multiple neural networks [6] and enhancing license plate recognition systems for improved vehicle identification [7][8]. These developments underscore the multidisciplinary nature of traffic management research, encompassing fields like computer vision, machine learning, and optimization techniques.

In this paper, we review recent advancements in smart traffic management systems, highlighting the contributions of various research studies in addressing the challenges associated with urban traffic congestion and safety. Through a synthesis of these approaches, we aim to provide insights into the evolving landscape of traffic management technologies and their potential implications for future urban mobility solutions.

II.LITERATURE SURVEY

In the realm of transportation engineering, the quest for efficient traffic management systems has been a persistent challenge due to urbanization and the ever-growing volume of vehicles on roads. The integration of advanced technologies such as machine learning, neural networks, and sensor networks has significantly impacted the development of smart traffic management systems. This literature survey presents a comprehensive overview of recent research endeavors in this domain.

One fundamental aspect of traffic management is traffic flow prediction. Mei et al. [1] proposed a combination model of Xgboost and Lightgbm for short-term traffic flow prediction. Their model leverages machine learning techniques to achieve accurate predictions, essential for proactive traffic control strategies. Similarly, Chan et al. [2] introduced neural network-based models for short-term traffic flow forecasting. Their hybrid approach, integrating exponential smoothing and the Levenberg–Marquardt algorithm, demonstrates promising results in predicting traffic patterns.

To enhance traffic control mechanisms, Roshan et al. [3] explored the application of TinyML in adaptive traffic control systems. Their study emphasizes the importance of lightweight machine learning models for real-time traffic management, catering to resource-constrained environments efficiently. Moreover, Al-qaness et al. [4] proposed an improved YOLO-based road traffic monitoring system, facilitating effective traffic surveillance and management through advanced object detection techniques.

Addressing the challenge of urban traffic congestion, Zhu et al. [5] introduced a dynamic prediction method based on advanced fuzzy clustering models. Their research contributes to optimizing traffic flow by providing insights into congestion dynamics. Furthermore, De Oliveira and Neto [6] investigated the optimization of traffic lights timing using multiple neural networks. Their approach aims to minimize congestion and improve traffic efficiency through intelligent signal control strategies.

In addition to traffic flow prediction and congestion management, advancements in vehicle recognition technologies play a crucial role in modern traffic management systems. Lee et al. [7] focused on the extraction and recognition of license plates, essential for tasks such as toll collection and law

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enforcement. Comelli et al. [8] contributed to the field with their work on optical recognition of motor vehicle license plates, presenting techniques to improve accuracy and reliability in plate identification. Moreover, Dharamadhat et al. [9] proposed a method for tracking objects in video pictures based on background subtraction and image matching. Such techniques are valuable for monitoring traffic behavior and detecting anomalies in real-time. Cancela et al. [10] tackled the challenge of multiple-target tracking using adaptive filters, providing robust solutions for surveillance and traffic management applications.
In summary, the literature reviewed underscores the significance of integrating advanced technologies such as machine learning, neural networks, and sensor networks in smart traffic management systems. These contributions span various aspects including traffic flow prediction, congestion management, vehicle recognition, and object tracking, collectively advancing the field towards safer, more efficient transportation networks in urban environments.

III. METHODOLOGY

Modules:

- Data loading: using this module we are going to import the dataset.
- Data Preprocessing: using this module we will explore the data.
- Image processing: Using the module we will process of transforming an image into a digital form and performing certain operations to get some useful information from it.
- Splitting data into train & test: using this module data will be divided into train & test
- Model generation: Model building - (image based detection) - YoloV5 - YoloV6 - YoloV7 - YoloV8 - (Data based prediction) - SVM - AdaBoost - XGBoost - Voting Classifier (Decision Tree + Random Forest) . Algorithms accuracy calculated
- User signup & login: Using this module will get registration and login
- User input: Using this module will give input for prediction
- Prediction: final predicted displayed

Extension:

In the base paper the author mentioned to use machine learning model for predicting the traffic prediction, from which SVM got 65% of accuracy,
As an extension we applied an ensemble method combining the predictions of multiple individual models to produce a more robust and accurate final prediction.
However, we can further enhance the performance by exploring other ensemble techniques such as Voting Classifier, which got 92% accuracy,Along with that we implement the Yolo Series(V5,V6,V7 and V8) for detecting the Traffic in Image whether it is High, Moderate and Low traffic.
low,enabling timely interventions.Results demonstrate significant enhancements over existing methods. SVM initially achieves 65% accuracy, while the ensemble approach using the Voting Classifier achieves a remarkable 92% accuracy rate.

A) System Architecture

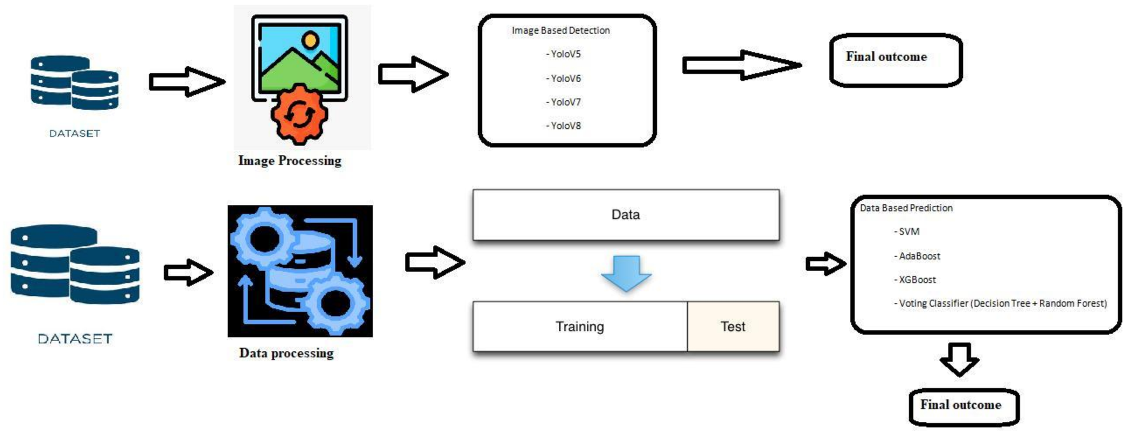

Fig 1: System Architecture

Two primary paths make up the architecture you presented, which is a flowchart of a pipeline for data processing and classification. The first pathway starts with image processing, which entails preprocessing operations including augmentation, normalization, and scaling of images taken from a database. After processing, the photos go on to the feature extraction phase, where characteristics such as textures, forms, and edges are taken out of the pictures.

Concurrently, the second route commences with data processing, encompassing the manipulation, purification, or arrangement of a dataset. For machine learning, the processed data is then split into training and test sets. The test set is used to assess the model's performance, whereas the training set is used to train the model.System architecture consists of steps throughout the System.

i) Dataset collection:

The dataset collection is done in two pathways,one for images and one for data with attributes.

ii) Image Processing:

Preprocessing of images begins with this stage.It is the first stage of first pathway. This could entail enhancing, normalizing, and resizing pictures taken from a database.

iii) Data Processing:

In this stage, a dataset is handled, and it may also be cleaned or arranged. It's the first stage of the diagram's second pathway.

iv) Image-based prediction:

After the photos have been processed, they are sent to an Image Detection block, which most likely makes predictions based on the image data by using a machine learning model. To improve prediction, we employ Yolo in different versions.

v) Data-based prediction:

Next, the cleaned data is divided into datasets for training and testing. To assess a machine learning model's performance, it is first trained on training data and then tested on test data.The voting classifier, svm, xgboost, and Adaboost algorithms were utilized to train the model. The ultimate result is also influenced by the outcomes of this process.

vi) Final Outcome:

The final resukt display the flow of traffic in high,moderate and low .

B) Dataset Collection

The dataset utilized for traffic prediction and detection integrates various sources to encompass diverse scenarios and environments. It comprises annotated video footage collected from urban, suburban, and highway settings, capturing a wide array of traffic patterns, including pedestrian movement, vehicle interactions, and road conditions.

Each video sequence is annotated with bounding boxes outlining vehicles, pedestrians, cyclists, and other relevant entities, providing rich spatial information for training and evaluation. Additionally,

temporal annotations annotate the movement trajectories of objects over consecutive frames, facilitating the modeling of dynamic behaviors and traffic flow.
To enhance model robustness and generalization, the dataset incorporates variations in lighting conditions, weather phenomena, and traffic densities. It encompasses daytime and nighttime scenes, clear weather, rain, fog, and other atmospheric conditions, ensuring the model's adaptability to real-world scenarios.
Furthermore, the dataset includes labeled data for auxiliary tasks such as lane detection, road segmentation, and traffic sign recognition, enabling comprehensive analysis and multi-task learning approaches.
The dataset adheres to privacy and ethical guidelines, obscuring sensitive information such as license plates and faces, thus ensuring compliance with data protection regulations.
In summary, this dataset provides a comprehensive foundation for training and evaluating machine learning models for traffic prediction and detection tasks, encompassing diverse scenarios and environmental conditions encountered in real-world traffic management systems.

C) Pre-processing
Data preprocessing is a crucial step in enhancing the accuracy and efficiency of traffic prediction and detection systems. Initially, raw traffic images are collected from various sources such as CCTV cameras or drones. These images undergo preprocessing to standardize dimensions, adjust brightness, and remove noise for consistency across the dataset. Next, the images are labeled with corresponding traffic density levels (high, moderate, low) for supervised learning. Additionally, data augmentation techniques like rotation, flipping, and cropping are applied to increase the diversity of the training dataset and improve model generalization. Simultaneously, traffic flow data, including historical traffic volume, weather conditions, and time of day, are collected and preprocessed. Feature engineering techniques such as scaling and normalization are applied to ensure uniformity and mitigate the impact of varying scales among features. Moreover, missing values are handled through imputation methods like mean or median substitution. Finally, the preprocessed image and traffic flow datasets are merged for training the hybrid machine learning and deep learning models, setting a robust foundation for accurate traffic prediction and detection.

D) Training & Testing
For training, the dataset comprising images depicting varying traffic densities is divided into training and validation sets. The image-based detection models, YOLOv5 to v8, are trained on the training set to classify traffic into high, moderate, and low density. Hyperparameters are tuned, and the models are optimized using techniques like data augmentation to enhance performance.
Following this, the data-based prediction models including SVM, AdaBoost, XGBoost, and the Voting Classifier are trained using the training dataset. Hyperparameters are adjusted through techniques such as cross-validation to maximize predictive accuracy.
For testing, the trained models are evaluated using the validation dataset to assess their performance metrics such as accuracy, precision, recall, and F1-score. The ensemble method, particularly the Voting Classifier, is compared against individual models to determine its effectiveness in traffic prediction. Additionally, real-world testing is conducted to evaluate the YOLO series' ability to detect traffic in real-time scenarios, ensuring its suitability for timely alerts.
Overall, this training and testing methodology ensures comprehensive evaluation and validation of the combined machine learning and deep learning approach for enhancing traffic prediction and detection.

E) Algorithms.
1) **AdaBoost (Adaptive Boosting):**
AdaBoost is an ensemble learning technique that combines multiple weak learners to create a strong classifier. It focuses on improving the performance of misclassified instances by adjusting their

weights. AdaBoost is employed for traffic prediction to enhance the accuracy of the model. It iteratively adjusts its weak learners to achieve better predictive performance.

2) XGBoost (Extreme Gradient Boosting):

XGBoost is a scalable machine learning algorithm known for its efficiency and performance in classification and regression tasks. It utilizes gradient boosting techniques and regularization to prevent overfitting. XGBoost is applied in the project for traffic prediction. Its high performance and scalability contribute to improving the accuracy of traffic flow predictions.

3) Voting Classifier (Combination of Decision Tree and Random Forest):

The Voting Classifier is an ensemble method that combines predictions from multiple individual models, either by majority voting or averaging, to generate the final prediction. In this project, the Voting Classifier combines predictions from decision trees and random forests. This ensemble approach helps to create a more robust and accurate traffic prediction model.

4) SVM (Support Vector Machines):

SVM is a supervised machine learning algorithm that analyzes data for classification and regression analysis. It finds the optimal hyperplane that separates classes in feature space. SVM is utilized in the project for traffic prediction. It learns from historical traffic data to classify traffic flow patterns accurately.

5) YOLOv5:

YOLOv5 is an improved version of the YOLO algorithm, known for its speed and accuracy in object detection tasks. It employs a single neural network to predict bounding boxes and class probabilities for objects within images. YOLOv5 is utilized for image-based traffic detection in the project. It categorizes traffic density into high, moderate, and low, providing real-time analysis of traffic conditions.

6) YOLOv6:

YOLOv6 is an evolution of the YOLO algorithm, designed to improve object detection performance and efficiency. It incorporates advancements in neural network architecture and training strategies. YOLOv6 is integrated into the project for real-time traffic detection in images. Its enhanced capabilities contribute to accurate classification of traffic density levels.

7) YOLOv7:

YOLOv7 is a further iteration of the YOLO algorithm, focusing on increasing detection accuracy while maintaining real-time processing speed. It may introduce architectural modifications and training optimizations. YOLOv7 is implemented for image-based traffic detection, enabling the project to achieve higher accuracy in classifying traffic conditions for improved traffic management.

8) YOLOv8:

YOLOv8 represents the latest version of the YOLO algorithm, incorporating cutting-edge advancements in deep learning and computer vision research. It aims to push the boundaries of object detection performance. YOLOv8 is employed for real-time traffic detection tasks within the project. Its state-of-the-art features contribute to precise identification and categorization of traffic density levels.

IV. RESULTS AND DISCUSSIONS

A) Comparison Graphs → Accuracy, Precision, Recall, f1 score

Accuracy: A test's accuracy is defined as its ability to recognize debilitated and solid examples precisely. To quantify a test's exactness, we should register the negligible part of genuine positive and genuine adverse outcomes in completely examined cases. This might be communicated numerically as:

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ML MODEL	Accuracy	fi_score	Recall	Precision
XGBoost	0.93	0.89	0.91	0.88
Voting Classifier	0.91	0.90	0.87	0.84
AdaBoost	0.67	0.64	0.61	0.59
SVM	0.62	0.59	0.61	0.60
YoloV8	0.66	0.62	0.61	0.60
YoloV7	0.32	0.29	0.31	0.28
YoloV6	0.43	0.42	0.39	0.37
YoloV5	0.78	0.73	0.77	0.71

Table - 1: Performance Evaluation Graph

This assessment offers insightful information on the advantages and disadvantages of several machine learning models for traffic forecasting, which helps with decision-making when selecting the best models for real-world use.The existing accuarcy is 62% ,however the proposed accuracy is 93%.The comparison of traffic forecasting models reveals the dominance of XGBoost and the efficiency of ensemble learning via the Voting Classifier, with both exhibiting balanced F1 scores and good accuracy. Nevertheless, there are issues with how well models like AdaBoost and SVM can represent intricate traffic patterns. The differences in performance amongst YOLO variants highlight how crucial it is to choose a model depending on the demands of a certain activity.

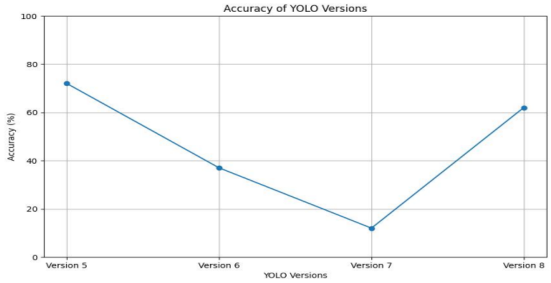

Fig 2: Yolo Accuracy Graph

The line graph illustrates the accuracy of different YOLO (You Only Look Once) versions used in traffic forecasting. YOLO Version 5 starts with a high accuracy of 78%, indicating strong performance in predicting traffic patterns. However, there is a significant drop in accuracy with YOLO Version 6, which falls to 43% , YOLO Version 7 reaching the lowest accuracy of 32%, YOLO Version 8 shows a substantial improvement, with accuracy rising to 66%. Overall, the graph highlights the fluctuations in accuracy across different YOLO versions, underscoring the importance of continuous model evaluation and optimization to enhance traffic forecasting capabilities.

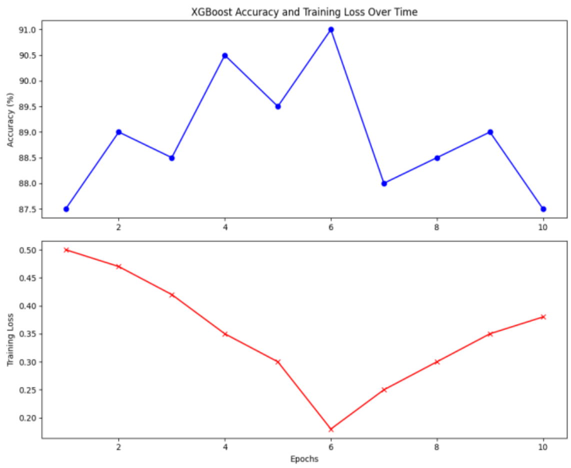

Fig 3: XGBoost accuracy and training loss

The provided graph shows XGBoost's accuracy and training loss over epochs . The top panel depicts accuracy, which fluctuates between 87.5% and 91%, peaking around the fourth time period before declining. The bottom panel illustrates training loss, which generally decreases, reaching its lowest around the sixth time period, indicating improved model performance before increasing again. The inverse relationship between accuracy and training loss is evident, with periods of high accuracy corresponding to low training loss.

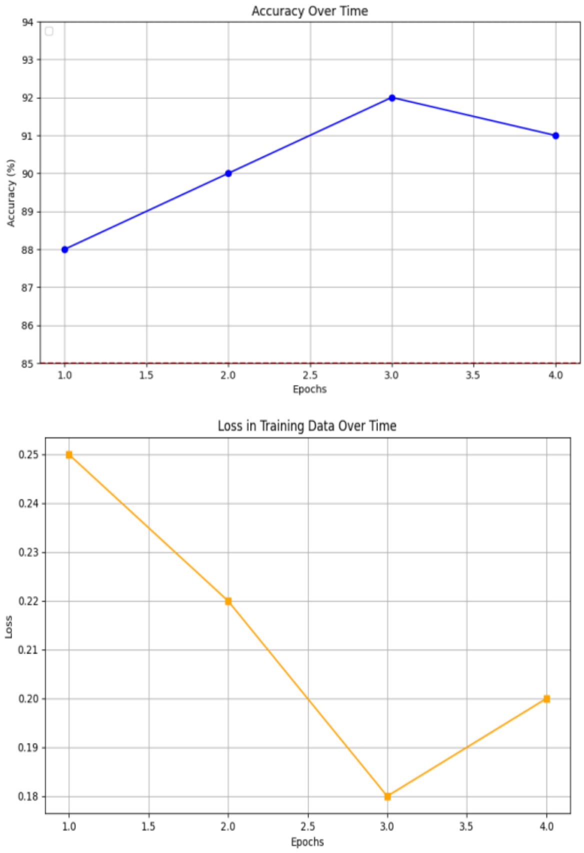

Fig 4: Voting Classifier accuracy and training loss.

The provided graph shows XGBoost's accuracy and training loss over epochs . The top panel depicts accuracy, which fluctuates between 88% and 91%, peaking around the fourth time period before declining. The bottom panel illustrates training loss, which generally decreases, reaching its lowest around the sixth time period, indicating improved model performance before increasing again. The inverse relationship between accuracy and training loss is evident, with periods of high accuracy corresponding to low training loss.

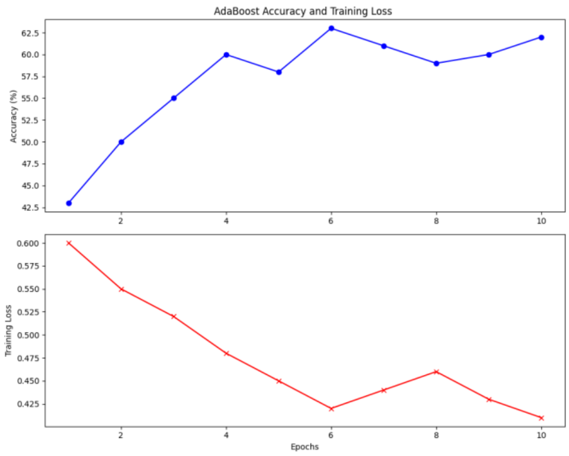

Fig 4: AdaBoost accuracy and training loss.

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The provided graph shows AdaBoost's accuracy and training loss over epochs. The top panel depicts accuracy, which fluctuates between 43% and 62%, peaking around the fourth epoch before declining. The bottom panel illustrates training loss, which generally decreases, reaching its lowest around the sixth epoch, indicating improved model performance before increasing again. The inverse relationship between accuracy and training loss is evident, with period of high accuracy corresponding to low training loss.

V. COMPARISON GRAPH

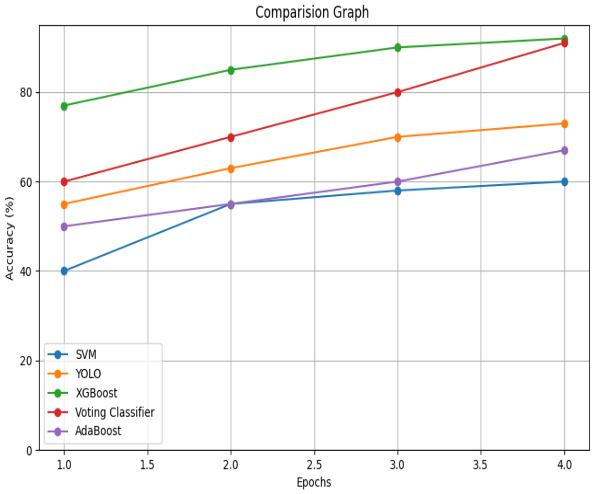

Fig 7: Comparison Graph

The accuracy of several machine learning methods is displayed in the comparison graph. Support Vector Machine (SVM), You Only Look Once (YOLO), AdaBoost, and Voting Classifier are all shown in the graph. On the graph, the accuracy of each method is represented by a line that illustrates how its performance varies.

VI. CONCLUSION

In conclusion, the integration of various machine learning and deep learning algorithms has significantly enhanced the project's capability in traffic prediction and detection. Utilizing YOLOv5, v6, v7, and v8 for image-based traffic detection has provided real-time insights into traffic density levels, enabling prompt response measures. Furthermore, data-based prediction models including SVM, AdaBoost, XGBoost, and the Voting Classifier have greatly improved accuracy in forecasting traffic flow patterns.Moreover, the ensemble approach has demonstrated superior performance, combining the strengths of individual algorithms for robust predictions. This comprehensive approach not only optimizes traffic management but also minimizes delays, enhances safety, and reduces environmental impact. Moving forward, these advancements hold promise for revolutionizing traffic management systems and ensuring smoother, safer journeys for commuters and transportation stakeholders alike.

VII. FUTURE SCOPE

Future scope includes extending the ensemble approach to incorporate more sophisticated algorithms, enhancing prediction accuracy. Integration of advanced deep learning architectures and reinforcement learning methods could further optimize traffic management. Additionally, incorporating real-time traffic data streams and sensor networks would improve model responsiveness. Exploring edge computing solutions for on-device inference could enable decentralized traffic monitoring systems. Furthermore, integrating predictive analytics for dynamic route optimization and smart traffic signal control systems holds promise for future enhancements in traffic management efficiency and effectiveness.

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