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A DEEP LEARNING ENSEMBLE APPROACH FOR THE DETECTION OF TRAFFIC ACCIDENTS IN SMART CITY TRANSPORTATION

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ABSTRACT

The dynamic and unpredictable nature of road traffic makes it necessary for smart cities to use efficient accident detection technologies in order to improve safety and streamline traffic management. This article presents a comprehensive exploration study of the various accident detection techniques that are currently in use. It sheds light on the nuances of other state-of-the-art methodologies while also providing a detailed overview of various types of traffic accidents, such as rear-end collisions, T-bone collisions, and frontal impact accidents. Our innovative technique presents the I3D-CONVLSTM2D model architecture, which is a lightweight solution that has been specifically designed for accident detection in smart city traffic surveillance systems. This is accomplished by merging RGB frames with optical flow information. The effectiveness of our model design is shown by the empirical analysis of the experimental research that we conducted. An amazing 87% Mean Average Precision (MAP) was achieved using the I3D-CONVLSTM2D RGB + Optical-Flow (trainable) model, which showed superior performance compared to its competitors. The issues that are provided by data imbalances are further elaborated upon by our results. This is especially true when dealing with a restricted number of datasets, road structures, and traffic situations. A sophisticated vision-based accident detection system that is ready for real-time integration with edge Internet of Things sensors inside smart urban infrastructures is the ultimate goal of our study, which sheds light on the road towards achieving this goal.

1.INTRODUCTION It is very difficult to identify and anticipate traffic accidents due to the interconnectivity of road networks, which presents a daunting obstacle. One of the most complex aspects of this problem is the dynamic influence that these accidents have, particularly at crossroads that are deemed strategically important. When it comes to solving these difficulties, the ever-evolving discipline of computer vision, which focuses on the analysis of spatial-temporal patterns, plays a crucial role by boosting our capacity to monitor and react to accidents in real time. This technological advancement is particularly pertinent in the realm of smart city development, where the incorporation of sophisticated accident detection and prediction systems into urban infrastructures has the potential to significantly improve safety, reduce traffic congestion, reduce the frequency of traffic accidents, and enhance the overall quality of life for city residents. Each year, there are 1.35 million deaths and 50 million injuries that do not end in death that are caused by road traffic accidents across the world [1]. The frightening numbers that have been presented here highlight the urgent need for innovative solutions to traffic management in order to increase safety and efficiency in urban transportation networks. The introduction of intelligent transportation systems has resulted in an increase in the need for intelligent transportation systems that are able to recognize and track a wide variety of items, including automobiles, motorbikes, and buses [2]. A substantial amount of progress has been made in the identification and isolation of objects in individual frames via the use of object detection in pictures. Despite this, video-based detection systems, which are becoming more widespread in a variety of applications, continue to struggle with the difficulty of using spatio-temporal data in order to achieve greater accuracy. Previous studies have investigated the use of temporal information for the purpose of feature extraction in the context of vehicle identification [3], and other methods have included this information into the post-processing phases of the process. There have been many different approaches created in order to enhance traffic safety and minimize the number of accidents that occur. One of these approaches is the employment of sensors for traffic monitoring and accident detection. These sensors may give significant data that can be used to anticipate future traffic conditions [2, 4]. The use of ultrasonic sensors for the purpose of autonomous road accident detection was suggested by Khalil et al. [4]. Two ultrasonic sensors are used in the proposed system in order to measure distance, and sound waves are utilized in order to identify potential collisions with obstructions. In spite of these developments, the majority of methods for monitoring road accidents in a timely manner continue to be difficult to implement and costly [2]. A growing number of modern technologies, including surveillance cameras, GPS, edge artificial intelligence, and the internet of things, are being used to create and implement deep learning algorithms for the purpose of detecting traffic accidents. Nevertheless, Recurrent Neural Networks (RNNs), which have typically been used in these systems, are not very effective when it comes to collecting spatial information from traffic data. This is because of intrinsic design restrictions that prevent them from processing sequences from various roadways independently. However, Graph Neural Networks provide a viable alternative by merging sequential and geographical data, which enables a more extensive study of traffic patterns. This is a significant improvement over traditional neural networks. In their study, Le et al. [5] highlight the significance of road-level accident prediction. They acknowledge that accidents are influenced by a combination of internal factors (such as the environment, the type of road, and the structure of the road) and external factors (such as the behavior of drivers, the weather, and the amount of traffic on the road). It is vital to differentiate between the detection of traffic accidents and the identification of traffic anomalies in order to bridge the gap between these sophisticated technology techniques and the practical elements of traffic management. Traffic anomaly encompasses a broader range of irregular

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traffic movements without collisions, while accident detection is focused on a narrow window of traffic accidents defined by occurrences of vehicle crashes and can be classified as a subset of traffic anomaly [6]. The perspective provided by camera angle plays a crucial role in how traffic accidents are interpreted and analyzed. This study focuses on accidents that were captured by traffic surveillance and dash cameras. The research has a special emphasis on occurrences that include collisions between various kinds of cars, as well as those that do not involve any collisions with other vehicles. Motorcycle accidents are not included in this study. The inherent difficulties in accident detection are brought to light by the diverse character of these accident scenes, as well as the multifarious variety of perspectives that are collected by these cameras. These difficulties are made much more difficult by extrinsic variables such as the ever-changing characteristics of the environment and the ever-changing nature of accident sites.

2.LITERATURE REVIEW

MULTI-GRANULARITY VEHICLE TRACKING FOR ANOMALY DETECTION AUTHORS: LI ET AL. This study presents a vehicle tracking technique using Faster R-CNN for object detection. The framework consists of an object detector, background modeler, mask extractor, and tracker. By incorporating both box and pixel-level tracking, the model enhances anomaly detection accuracy. However, the reliance on tracking makes it computationally expensive and difficult to implement in dense traffic conditions.

UNSUPERVISED ANOMALY DETECTION USING VEHICLE TRAJECTORIES AUTHORS: ZHAO ET AL. The findings of this study provide an unsupervised unsupervised anomaly detection system that is based on vehicle trajectories. To reduce the number of false positives that are brought on by the system, a multi-object tracker is used. errors in object detection. This technique has a number of benefits, the most important of which is that it does not need labeled datasets, which enables it to be adapted to a variety of diverse situations. The tracking-based technique, on the other hand, results in an increase in processing cost, and performance is strongly reliant on the accuracy of trajectory estimate.

REAL-TIME TRAFFIC ANOMALY DETECTION USING YOLO AND FEATURE TRACKING AUTHORS: MANDAL ET AL For the purpose of identifying stopped cars and accidents on the side of the road, this research suggests a traffic anomaly detection system that makes use of a pre-trained YOLO model in conjunction with a feature tracker. A post-processing in the The module incorporates K-means clustering and closest neighbors in order to achieve higher levels of accuracy. Despite the fact that this method is both quick and accurate, it necessitates a significant amount of training and a high level of processing resources. Furthermore, it is possible for it to produce false positives owing to stationary objects that are not associated with accidents.

SPATIAL-TEMPORAL MATRIX FOR ANOMALY DETECTION IN TRAFFIC VIDEOS AUTHORS: BAI ET AL Through this study, a spatial-temporal matrix is presented with the purpose of enhancing the identification of anomalies in traffic situations. By transforming strip trajectory analysis into spatial location research, the system creates new possibilities. enhancing the accuracy of the detection of abnormalities starting and stopping at certain periods. A perspective detection module and a backdrop modeler are also included in the framework. The 2019 NVIDIA AI City Challenge was won by this method, however it has significant computing needs, is sensitive to camera changes, and requires sophisticated preprocessing in order to do accurate trajectory analysis. Despite these drawbacks, the method was effective in achieving the top ranking.

3.EXISTING SYSTEM

- Cai et al. [14] investigated the use of clustering approaches to identify deviations in typical traffic patterns in order to determine the identification of abnormal traffic flow. In earlier research, such as that conducted by Morris and Trivedi [15], the Hidden Markov Model was used for the purpose of intelligently describing scenes via the utilization of spatiotemporal dynamics. More recent research has focused toward using machine learning and deep learning approaches for the purpose of extracting spatio-temporal information from video streams [16], [17], [18]. This has resulted in improvements such as integrating convolution layers with LSTM architectures for increased performance [18], [19], [20]. As can be observed in Carreira and Zisserman's [21] introduction of the twostream inflated 3D ConvNet (I3D) designs for better video input categorization, the investigation of complicated networks in accident detection has also been a major topic of discussion. This part of the article dives into a variety of approaches and models that have made important contributions to the process of identifying and evaluating traffic incidents within the context of smart city platforms.
- Le et al. [5] brought attention to the fact that traffic accidents are a substantial contribution to the number of deaths and economic losses that occur in modern society. As a solution to this problem, the authors present the Deep Spatio-Temporal Convolutional Network (DSTGCN), a model that makes use of deep geographical and temporal data in order to forecast the occurrence of traffic accidents. The intricate, non-Euclidean structures that may be discovered in graph data have been successfully mapped by the discipline of Graph Neural Networks, which is the subject of a rapidly expanding area of research.
- The study conducted by Wang et al. [22] looked at the dynamic intricacies of road networks and asserted that the effect of these networks goes beyond simple proximity analysis. The Spatial Temporal Graph Neural Network (STGNN) was created by them in order to efficiently describe long-range global relationships in traffic flow. A positional graph neural network layer, which is meant to capture spatial interactions, a recurrent neural network layer, which is designed to handle temporal dynamics, and a transformer layer are the three major components that make up this novel network. On the idea that traffic is present, the architecture is constructed.

3.1.DISADVANTAGES By introducing a novel object detection algorithm that was developed specifically to handle video data and mitigate the biases of traditional models, Yang et al. [9] attempts to improve object detection models by taking into consideration the drawbacks of object detector algorithms in single frames that are highlighted in the research of Wang et al. [22]. This is done in an effort to improve object detection models.

3.2. PROPOSED SYSTEM

In the area of accident detection, the merging of machine learning (ML) and deep learning (DL) approaches has resulted in considerable advancements. These technologies are especially effective at processing huge accident datasets, which enables the identification and categorization of occurrences based on important criteria such as speed, direction, and the kind of vehicle involved. For the purpose of predicting the probability of accidents, Singh et al. [27] suggested a system that makes use of deep representation extraction by means of autoencoders in conjunction with an unsupervised learning model, such as the Support Vector Machine (SVM). For the purpose of enhancing prediction skills, this technique highlights the possibility of integrating machine learning models with advanced feature extraction. Deep learning models, which are complementary to machine learning, provide interesting pathways for the identification of accidents in real time. In order to detect prospective risks and accident situations, these models make use of camera systems to continually watch highways. They then utilize powerful image recognition and video processing algorithms to identify these potential factors. Having the capacity of deep learning models to do sophisticated video data analysis in real time is very necessary for the timely identification of accidents, which is an essential component in the prevention and mitigation of accidents. Zadobrischi [41] focuses on the incorporation of traffic monitoring systems into intelligent transportation systems (ITS) in order to effectively manage traffic and lessen the detrimental effects of traffic congestion and accidents on the roads in real time by making use of video and image data. An approach known as Dynamic-Spatial-Attention (DSA) Recurrent Neural Network (RNN) was suggested by Chan et al. [42] for the purpose of predicting accidents in dashcam recordings by taking into account the trajectory and velocity of the vehicle. The algorithm that was built includes an object detector that can dynamically collect minor signals and the temporal connections of these cues in order to anticipate accidents two seconds before they actually take place. A three-step hierarchical architecture is presented by Ghahremannezhad et al. [43] for the purpose of identifying traffic accidents that occur at crossings via the use of surveillance cameras. During the process of object tracking, a one-of-a-kind cost function is applied in order to manage occlusions, overlapping objects, and changes in the geometry of the object. In general, our technique combines the deep learning approach with transfer learning in order to produce a system that is comprehensive, efficient, and accurate for the identification of traffic accidents.

3.3. ADVANTAGES

• Advanced Vision-Based Accident Detection System:

We introduce an innovative vision-based accident detection system, specially optimized for realtime implementation on edge IoT devices such as Raspberry Pi. This system is designed to minimize computational overhead, making it highly suitable for smart city infrastructures and traffic surveillance systems. Its lightweight architecture successfully blends computational efficiency with practical applicability, establishing a cost-effective, reliable, and deployable solution for the modern smart city.

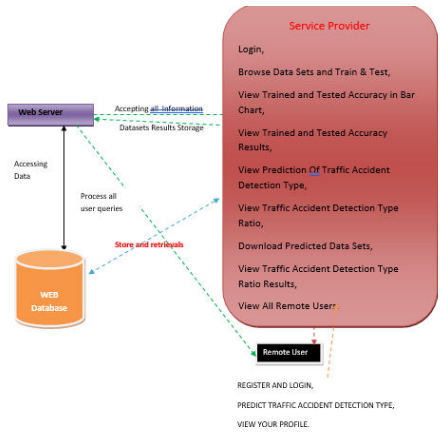
• Novel Model Architecture: Our research proposes a distinctive model architecture that extracts RGB frames and optical flow information from video sequences. Incorporating transfer learning techniques and the CONVLSTM2D architecture, this model significantly enhances accident detection performance, distinguishing our approach from existing methodologies.

• Specialized Benchmark Datasets: Addressing the lack of benchmark datasets in the accident detection domain, we have curated two specialized datasets: the Traffic

Camera Dataset and the Dash Camera Dataset publicly available at [7] and [8]. These datasets are specifically de signed for accident detection and offer a diverse range of scenarios and roadway designs, serving as a valuable resource for ongoing research and development in this field

4.IMPLEMENTATION

4.1.SYSTEM ARCHITECTURE



4.2. MODULES

SERVICE PROVIDER

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Browse Data Sets and Train & Test, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Traffic Accident Detection Type, View Traffic Accident Detection Type Ratio, Download Predicted Data Sets, View Traffic Accident Detection Type Ratio Results, View All Remote Users.

VIEW AND AUTHORIZE USERS

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

REMOTE USER

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT TRAFFIC ACCIDENT DETECTION TYPE, VIEW YOUR PROFILE

5.RESULTS

Fig: Running the Project

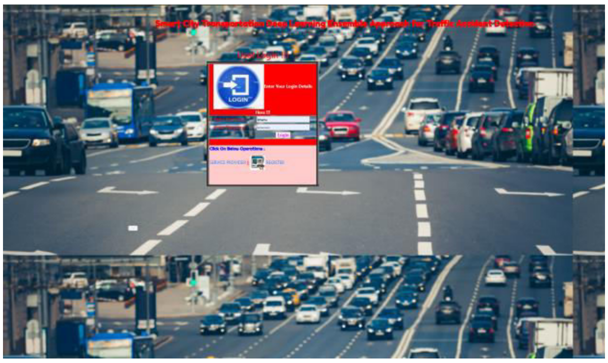


Fig: Login Page For Both Remote User and Service Provider

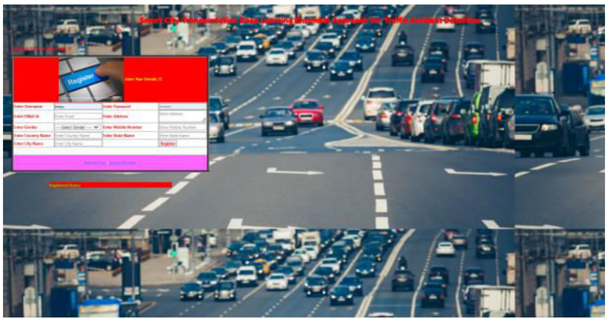


Fig: User Registration Page

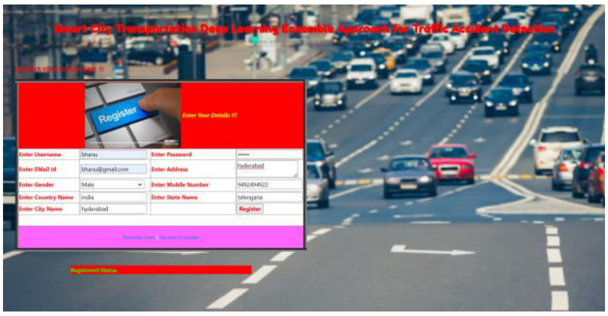


Fig: Passing User Details For Registration

Fig: User Registered Sucessfully

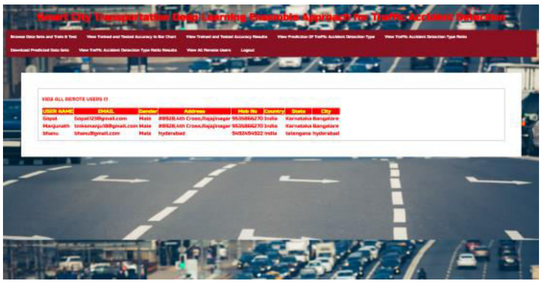


Fig: Passing Credentials For admin

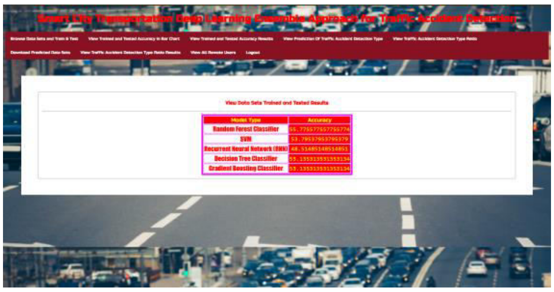


Fig: Training Data Set By Using Machine Learning Algorithms

Fig: Displaying accuracy in Bar Charts

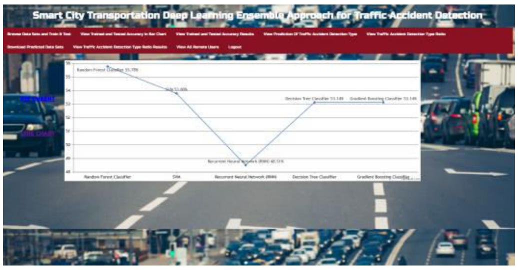


Fig: Displaying accuracy in line chart

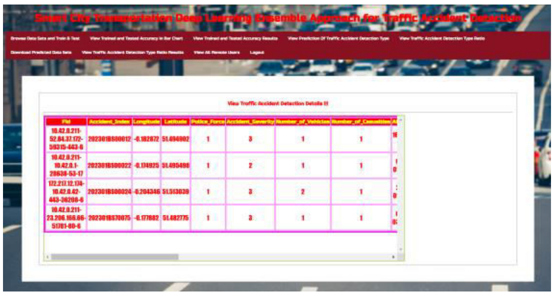


Fig: Accident Prediction Results

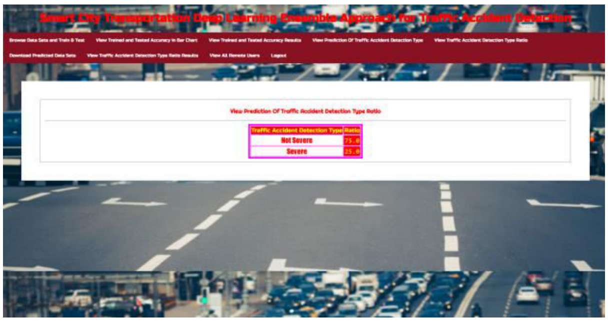


Fig: View Prediction of Traffic accident Detection type ratio

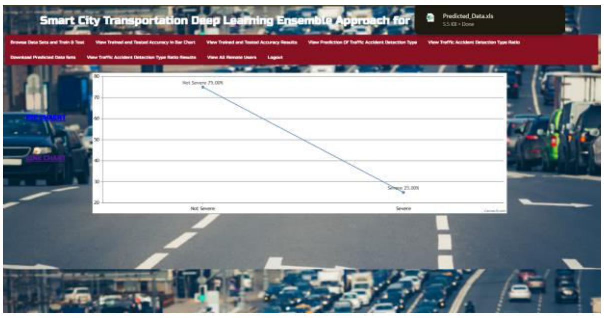


Fig: Displaying Detection ratio Result

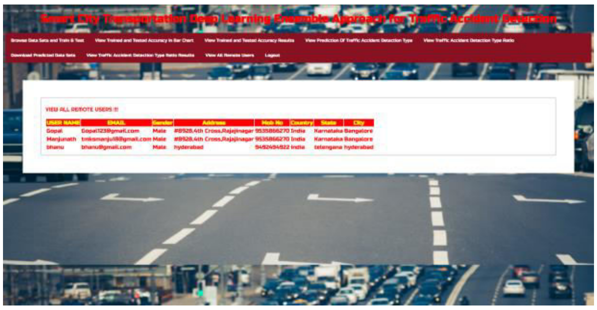


Fig: Displaying All Users

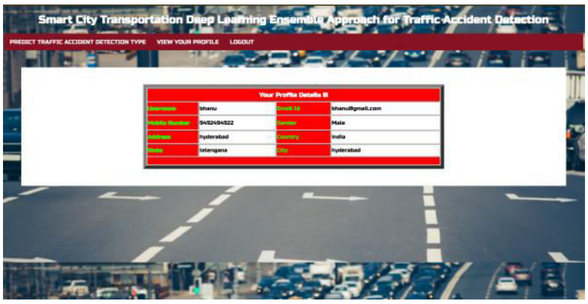


Fig: login by using User credential's

FIG: PREDICITNG DATA

CONCLUSION

The techniques of accident detection have seen tremendous development, beginning with the classic human-based reporting and progressing to the more current automated systems. These cutting-edge technologies, which make use of sensors, machine learning algorithms, and computer vision, constitute a paradigm change in the field of accident detection. In particular, computer vision-based systems stand out because to their capacity to detect in real time and their flexibility to a wide variety of road circumstances. Considering the rapid pace at which technology is advancing, these systems are well positioned to become vital instruments for the improvement of traffic safety. Our study led to the creation of the I3D-CONVLSTM2D Trainable RGB + Optical Flow model, which exhibited remarkable performance, with an accuracy of 0.80 and a mean average precision of 87%. This model was the culmination of our efforts. The capability of our model to identify the characteristics of traffic accidents in the middle of intricate traffic situations is a substantial advancement in the field of automated accident observation. Traffic accidents continue to be a key cause for worry when it comes to safety, especially in places with a high population density, since they are responsible for a significant share of deaths. In order to solve this issue, our research included the creation of a vision-based accident detection system that was designed specifically for real-time deployment on edge Internet of Things devices like Raspberry Pi. After becoming aware of the inherent difficulties associated with such a strategy, most notably the enormous amount of data that is required, we decided to take the initiative to compile a new accident dataset. In order to provide researchers with the freedom to expand or alter our basic architecture for accident detection, this resource may either be used as a standalone tool or as a supplement to datasets that are already in existence. A significant amount of computing effort is required to train the I3D two-stream network using the Kinetics dataset, which has 25 million parameters, and its long training procedure, which spans 32 GPU1s and 120 thousand steps. This is in contrast to our model, which was trained on an Ubuntu 20.04.2 LTS machine that used two GPUs, each of which had 11 GB of memory. Our model was built to be efficient and resource-conscious. In order to demonstrate our dedication to efficiency, the model specs are as follows: the RGB model has a total of three million parameters, and the I3DCONVLSTM2D Trainable RGB + Optical comes with nine million parameters. In a nutshell, our research helps to bridge the gap between computational efficiency and practical application by providing a reliable accident detection system that is both cost-effective and suited for smart city infrastructures. Our research opens the door to the possibility of surveillance systems that are more easily available and more pervasive. Particularly noteworthy is the fact that our model's simplicity, efficiency, and decreased computing needs serve as a testimony to our goal of developing lightweight but efficient solutions for major societal concerns. This is particularly true when compared to heavyweights such as I3D.

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