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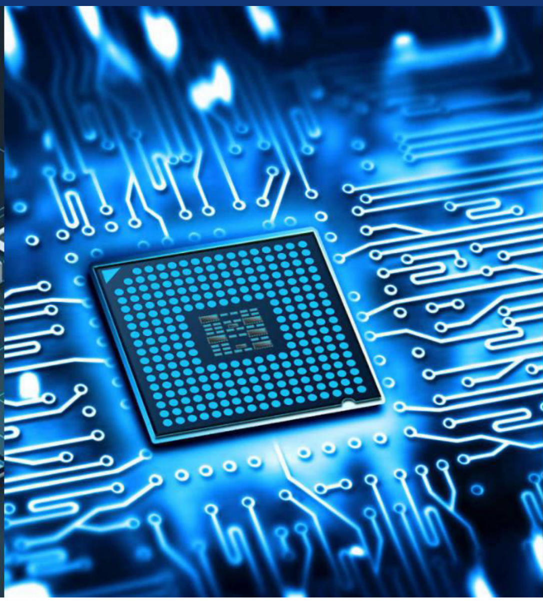

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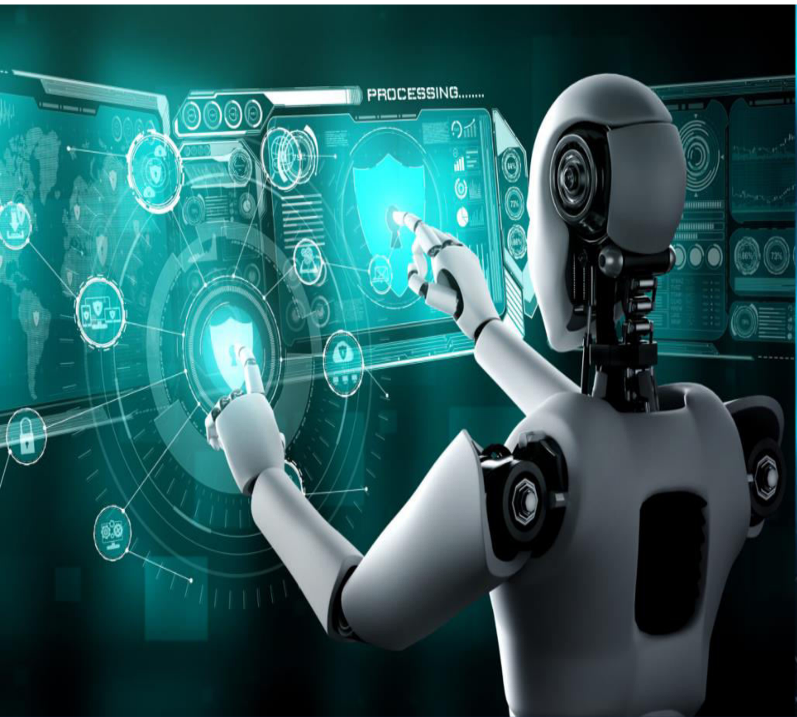

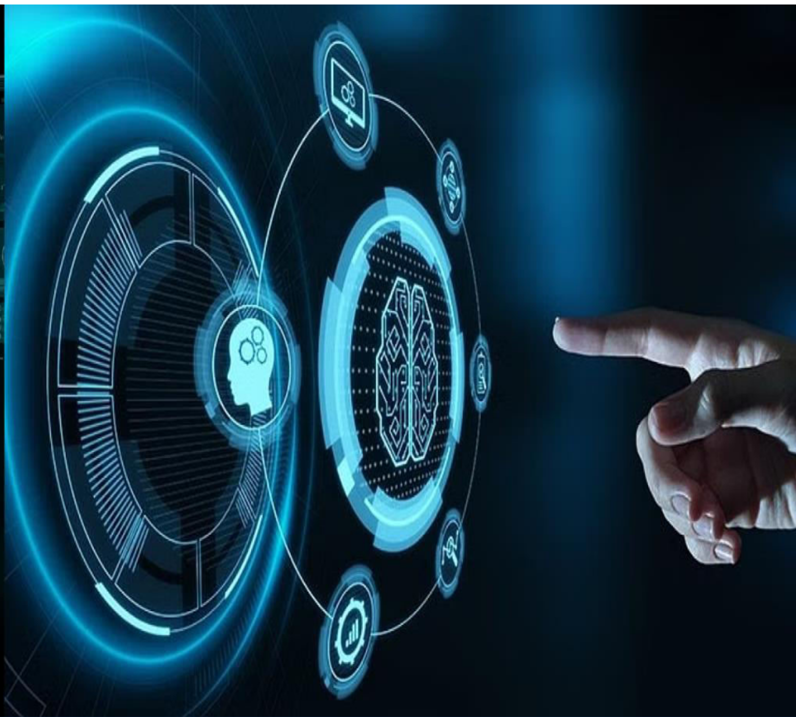

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Traffic Management Using Deep Learning Algorithms

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ABSTRACT: The problems associated with the prevention of road accidents that occurred in the different localities can be suppressed using data availability. Machine learning algorithms can be employed to integrate and categorize databases collected from educational institutions and government websites. This integration process enables the potential estimation of accident locations, enhancing the efficiency of accident detection and response. In the research proposal, a hybrid Deep Learning-based Bangalore Metropolitan Transport Corporation (BMTC) transportation system is proposed. This system utilizes a combination of techniques to categorize data into various segments, including the count of bus stations, city buses, accidents, and routes within the BMTC transport network. This research employs a combination of Support Vector Machine (SVM) and Convolution Neural Network (CNN) deep learning algorithms to analyze and categorize BMTC bus information. The focus includes identifying the number of accidents, police cases booked, bus timings, depot count, road area details, and platform numbers. CNN is specifically utilized to determine the availability of buses based on routes, geographical areas, and depots. Based on these three results, the SVM is going to predict the best or excellent, or average bus. In the pre-processing stage, the given databases are converted into text/images/textures and also remove all unnecessary features with help of the Power Business Intelligence (BI) software tool. In the second state, cleansing and extraction of data are extracted; the features are concerning buses information available in Bangalore. The third stage involves implementing a learning system to forecast the selection of superior-quality buses for the public. Here the deep learning-based model is established for an end-to-end mapping between the training and accident prediction. Initially, training data is prepared and processed before being fed into the neural network as input. Then, statistical significance is prioritized based on details extracted using predetermined and applied as the activation function. In conclusion, accident prediction utilizes frequency of incidents, location data, and timing information. Here CNN network structures comprise of only three layers and its performance metrics are validated using detailed prediction accuracy.

KEYWORDS: Road accidents, Prediction, Deep learning, Bus transport, SVM, CNN.

I. INTRODUCTION

Numerous previous studies [1-5] have demonstrated that traditional statistical classifier/predictor models utilizing machine learning techniques often provide less timely information as they learn from individual events within available data. In contrast, deep learning models, characterized by multi-layered neural networks, have the capability to extract more comprehensive insights from data, resulting in higher prediction accuracy. In this paper, we introduce a deep learning-based classification approach aimed at exploring the potential for predicting public bus transport accidents. The proposed method leverages the following aspects:

- To carry out 3 layered training set models using the CNN model that utilizes multi-model attributes and relevant residual blocks.
- To validate the statistical significance of correlative analyses and their retention in overall prediction accuracy.

Formation of zones and sub-zones: In this study, the metropolitan region is conceptualized as a network comprising nodes and links. Here, the nodes represent distribution centers, while the links denote the routes connecting these distribution centers. The region is primarily focused with Static Agents (SA) operated in the depot, and further utilizes the strategies of coordinate to logically split up the area into a required number of regions as well as sub-zones. Mobile agents (MAs) are formed and delivered to zones by a SA deployed at the depot. In an urban area, the responsibilities of SA's at the depot are as follows:

- Sub-zones, and logical zones, are created.
- It generates and deploys MAs to all areas in a city on a conventional basis to gather resource data, traffic density, statistical data, and other details.

It examines as well as forecasts the accurate scenario and thereby necessitates the fluctuations in traffic density, resource usage, as well as travel time in every area of a metropolitan region. In this research work, we used all of the

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parameters mentioned above to evaluate the traffic load in an area. This paper is organized as follows: Section 2 discusses various highway traffic and accident prediction techniques and their metrics in Traffic Safety Administration applications. Various stages of proposed data set computation and characteristics have been analysed in Section 3. Section 4 explains the CNN model used for the residual extraction process and its associated efficiency, followed by the conclusion.

II. RELATED WORK

An investigation aims to assess the impact of social media which will aid mobility operations in recognizing the day-to-day difficulties that individuals face and proposing an effective solution and pre-processing approaches on transit analysis and forecast is discussed in this research to perform better. Pre-processing with the bigram algorithm outperforms the other approaches, notably Support Vector Machine and Naive Bayes [1] when assessing social media linked transit opinion data. We cover studies and implementations that include UAS in mobility research and practice for this article, to lay the groundwork for effective understanding and implementation of UAS-related monitoring systems in urban traffic design. The research that was looked at was divided into several categories based on their application in the engineering field. Both on a theoretical and empirical level, existing and future challenges are identified and analysed [2]. By categorizing the links and personality of the journals in Web of Science [3], we select the TOP 5 core papers of these 12 topics and extract their variety of unique areas. Using a customized k-nearest neighbour algorithm, this research presents a data-driven interpolation approach for road segments based on temporal and spatial association. Furthermore, every section's topological feature is preserved; that is, the continuity of traffic properties captured by each sensor is preserved, boosting restoration precision. This research compares the suggested method's results and analyses to those of others, demonstrating that it outperforms them in practically all missing types, missing ratios, day types, and traffic conditions and if the data type is missing are not identified the algorithm shows accurate and stable imputation performance [4].

Traditional urban design systems are based on factors such as the district's GDP, employment rate, population size, and data from questionnaire surveys, among others. Urban data can now be used effectively for urban planning because of advances in the digital platform. To that end, this study introduces AttractRank, a district attractiveness ranking methodology based on taxi big data acquired from Guangzhou, China, which is the first to employ taxi big data for district evaluation. The capital town of Guangzhou is separated into several regions by constrained K-means and the basic PageRank is extended to include the taxi's origin-destination points to create the OD matrix. Hence, we establish a pattern of how district attractions vary over time, as well as important discoveries about urban life. The software application is now publicly available at http://qgailab.com/ieee/attractrank/index.html [5]. Because of the dynamicity of massive data streams, high-frequency unlabelled data production from heterogeneous data sources, and the volatility of traffic conditions, existing artificial intelligence approaches that work in isolation have evident limits in establishing a holistic platform. To solve these issues, we present a large-scale smart traffic management platform (STMP) based on unsupervised online progressive machine learning, deep learning, and deep supervised learning. The algorithm has been widely tested on the arterial road network of Victoria, Australia [6], using 190 million records of embedded sensors network traffic data collected by 545,851 passengers and accompanying datasets. We gather data on transportation carbon emissions the traditional method by measuring the burning of fossil fuel in the transport sector and real-time, as precise fossil fuel combustion is extremely difficult to attain. Based on the temporal databases we anticipate real-time and fine-grained transportation carbon pollution information for the entire city under this article. To acquire the properties of data analysis and infer transport carbon emissions, we propose a three-layer perceptron neural net (3-layer P NN). The method outperforms three well-known machine learning algorithms (Gaussian Naive Bayes, Linear Regression, and Logistic Regression) as well as two deep learning algorithms (Stacked Denoising Autoencoder and Deep Belief Networks) [7].

In this study, a novel framework for future data-driven railway condition monitoring systems is introduced. We suggest an edge processing unit for this objective, which consists of two parts: a data categorization model that divides Internet of Things (IoT) data into maintenance-critical data (MCD) and maintenance-non-critical data (MNCD). Three separate data sets under varied operating settings were used to satisfactorily validate the performance of our suggested approach [8]. To study and anticipate traffic flow in Los Angeles County, the article uses a traffic database. This article's primary strength is to provide a clear picture of how large-scale traffic data sets can be stored and handled utilizing Big Data technologies such as Hadoop and its ecosystem. Azure ML Studio is used to display the prediction analysis with classifiers for the test flow set of data and interpreted results by accuracy, precision, recall using BI tools [9]. In this study, we assess the performance of the Bangalore Metropolitan Transport Corporation (BMTC), with a focus on the

BMTC's quality bus services in Bangalore. Two separate methodologies are used to assess the performance of bus services by ratios and financial indicators and the performance of bus depots using data envelopment analysis (DEA). As the analysis shows that depot 13 is most significant for improvement [10][11].

To fulfill rapidly-growing mass mobility needs, it is critical to maintain and improve public transportation systems in Indian cities. Numerous factors affect the process of public transit operations. Using data for the period, this study evaluates the performance of Bangalore Metropolitan Transport Corporation's premium transport services. The majority of depots are efficient, according to the research, but other routes have great potential for expansion [12].

With ETM-based time-series data, this research investigates the use of the time process for predicting public bus travel demands. The study's data comes from the Kerala State Road Transport Corporation's (KSRTC) ticket sales transaction database, which was kept at the Trivandrum City depot in the Indian state of Kerala from 2010 to 2013. The four time-series models are associated using Mean Absolute Percentage Error (MAPE) and goodness is determined by information criteria [13]. The study described in this section is part of the Advanced Urban Public Transportation System project, which is financed by the Department of Science and Technology. The suggested solution addresses issues such as GPS outages, bus schedules and stops being unknown, and real-time traffic data being unavailable along the bus line and system are evaluated by multiple-trip over a 32-kilometer-long route during the peak and off-peak hour traffic situations. The bus-stop detection precision of 75% and arrival time prediction error of 7% (5 minutes) has been reported and scalability assessment of the system supports the transit of more than ten thousand buses and over one million subscribers/commuters [14].

This research used big data analysis and the computer software SPSS to investigate the effects of two bus fare adjustment policies in Beijing on the rate of urban public transportation sharing, and then made recommendations for bus fare reform in Beijing [15]. The study focuses on Croatia and demonstrates the importance and compatibility of social media-related data with official data for transportation and tourism planning [16]. Data science developments have permeated every aspect of transport science and engineering, leading to data-driven improvements in the transport industry. This paper explains how data from various ITS sources may be used to train and update data-driven models for more successfully operating ITS assets, systems, and processes; in other words, how data-based models may become completely operational. Because the basis of our study is the firm notion that most learners will have to adjust to the ever-changing phenomena situation underpinning most ITS applications, we purposefully broaden method learning to be reactive. We offer a glimpse into current Data Science research lines that could lead to significant breakthroughs in data-based ITS modeling, bridging the gap between practicality and actionability, ultimately [17].

The network architecture and early results of pNEUMA, a first-of-its-kind effort to produce the most comprehensive urban dataset to analyze overcrowding, are discussed in this paper. The experiment's goal is to use unmanned aerial vehicles (UAS) to record traffic streams in a multi-modal congested environment above an urban setting, allowing for in-depth analysis of crucial traffic phenomena. The pNEUMA project creates a prototype system that opens up a world of possibilities for researchers, many of which are outside the scope of the authors' interests and experience. The open research institute produces a one-of-a-kind traffic congestion observatory, one-order-of-magnitude larger than anything previously available, that researchers from all disciplines can use to design and test our predictions [18]. Transportation management can increase its analysis and decision-making processes by leveraging the growing availability of trajectory datasets. This paper looks at trajectory data through the eyes of a road transportation agency looking to improve its analysis by gathering morphologies and providing a literature review illustrating applications of trajectory data in six areas of road transportation systems analysis. It also visually investigates 20 million GPS traces in Maryland, USA, highlighting existing and offering new programs for trajectory data [19]. The origins and properties of big data and intelligent transportation are first discussed in this study. Following that, the architecture for performing big data analytics in ITS is addressed, which includes a summary of data sources and collecting methods, data analytics methodologies and systems, and big data user preferences. Several case research of big data analytics implementations in intelligent transportation systems are presented, including road traffic accident analysis, road traffic flow forecasting, urban transport service plan, personal travel route plan, passenger rail control and management, and project delivery. Moreover, several open issues of using big data analytics in ITS are discussed in this paper [20].

The overall pattern of traffic system design is intelligent traffic systems. The goal of maximizing the organization of intelligent transportation, as well as scientific decision-making and intelligent travel, can be fulfilled through data analysis

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and mining of large data of traffic management. The goal of an intelligent transportation system (ITS) is to use modern high and new technology to track traffic issues holistically. The article goes into the theory, process, and technology that went into the development of its big data analysis and architecture [21]. The foundation of developing societies is mobility by road. About 20–50 people are injured in road traffic crashes each year, with many of them becoming disabled as a result of their disabilities [1]. Globally, these catastrophes result in significant socioeconomic harm [2]. Children from shattered homes are more likely to become criminals or victims of crime. Family's financial situations are likely to be affected by the death of family members, denying children a suitable upbringing. Our countries lose talents as a result of these fatalities, and the social security system bears a greater strain [22]. As it solves the limits of the old transport system, the Intelligent Transportation System (ITS) has been recognized as an effective element and warmly received for the global buildings. A Dynamic and Intelligent Traffic Light Control System (DITLCS) is presented in this study to increase the efficiency of the traffic light control system by taking real-time vehicle data as input and dynamically adjusting the traffic signal length. As per the traffic data, a deep reinforcement learning model is presented to switch the traffic lights in various stages (Red, Green, and Yellow), and a fuzzy inference system picks one mode from 3 steps (FM, PM, and EM). We tested DITLCS using a simulation game on a map of Gwalior, India, using an open-source model called Simulation of Urban Mobility (SUMO). On many control factors, the results show that DITLCS is more efficient than other state-of-the-art methods [23]. In terms of public mobility administration, security, and other challenges, an intelligent transportation system (ITS) is critical. This paper proposes a road traffic detection approach on the edge node ensemble learning to resolve this challenge. To begin, we suggest a vehicle detection method based on the YOLOv3 (You Only Look Once) model, which has been trained on a large amount of traffic data. Afterward, the Deep SORT (Deep Simple Online and Real-time Tracking) system is fine-tuned for multi-object traffic monitoring by retraining the extracted features. Finally, to assess traffic flow, we present a real-time vehicle tracking counter for cars that integrates traffic signs and automatic vehicle techniques. Our algorithm can recognize traffic flow with an average response time of 37.9 FPS (frames per second) and an accuracy rate of 92.0 percent on the edge device, according to the test findings [24]. To successfully restore traffic flow and reduce major injuries and fatalities, primary sources of traffic incidents and terms of the process are required. This problem can be solved by combining a sophisticated data categorization model with a large amount of traffic data. Using ontology and latent Dirichlet allocation (OLDA) and bidirectional long short-term memory, a social network–based, real-time monitoring system for traffic accident identification and condition analysis is provided in this research. To begin, the query-based web browser successfully collects flow data on social sites, which is then transformed into a meaningful way by the data preparation component. Finally, the suggested OLDA-based topic modeling technique tags each phrase dynamically to identify the precise traffic data. Furthermore, the ontology-based approach to event recognition identifies traffic events from traffic-related information. OLDA and BiLSTM are compared to existing topic modeling approaches and conventional classifiers utilizing deep feature frameworks, accordingly, using traffic-related data. Our immediate notification state-of-the-art methods, with a 97 percent accuracy rate. In contrast to other current systems, this conclusion means that the model is more efficient for traffic event recognition and terms of the process [25].

III. PROPOSED METHODOLOGY FOR TRAFFIC MANAGEMENT USING DEEP LEARNING ALGORITHMS

The proposed Machine Learning-based BMTC transportation system is a hybrid techniques-based system for segregations of city buses and to identify the most recent and most used/booked buses depending on framework matches the interacting user to the users of social media platforms exhibiting similar taste. In this research, combinations of deep learning algorithms are used to analyze and identify the BMTC buses' information in terms of the number of accidents, number of police cases booked, timings of the buses, number of depots, road area information, and number of platforms. The CNN is to identify the number of buses information in Bangalore and their types of buses, CNN is to identify the number of people who got accidents and other information. The combination of CNN is to identify, the number of buses available based on the routes, area, and depots. Based on these three results, the SVM is going to recommend the best or excellent or Average bus to public people. In the pre-processing stage, the given databases are converted into text/images/textures and also removes all unnecessary features with help of MATLAB 2017a and Power Business Intelligence (BI) software tool. In the second state, features are extracted using CNN, the features are in terms of buses information's available in Bangalore. The third stage is the learning system for the recommendation of final better/good/excellent buses to people. The complete database is exported into Power BI and is separated and stored in Power BI for the generation of reports in terms of different Visualizations. Fig. 1 shows Proposed block diagram of prediction of number accidents and others BMTC buses information based on deep learning algorithms.

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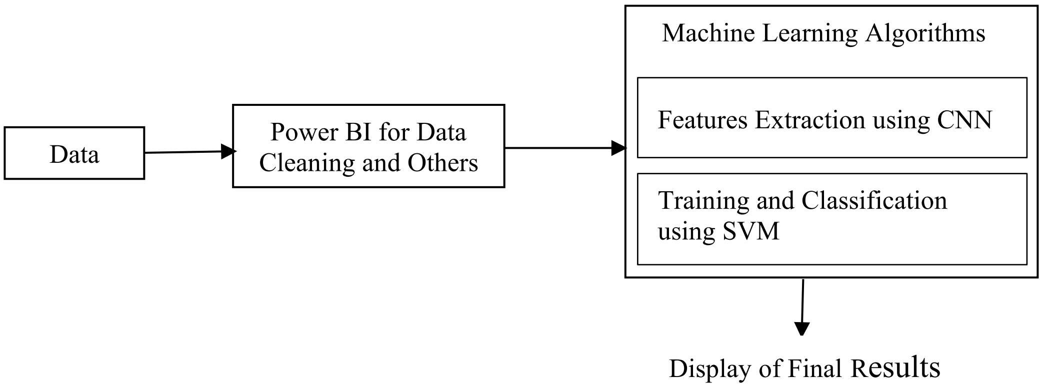

Fig. 1. Proposed block diagram of prediction of number accidents and others BMTC buses information based on deep learning algorithms.

IV. RESULT AND DISCUSSION

A. *CNN Model for Accident Risk Prediction:*

Public Transportation data: Crashes caused by public Transportation can be examined due to its scheduled timing and can save significant losses to the people and also avoid property damage and traffic congestion within the city limits. Sample data sets are shown in table 1. By identifying the specific location or route which can cause maximum cases to appropriate preventions can be made to narrow down the accidental deaths. Transport data collected constitutes various measures such as route number, bus speed, and a number of cases for every year from Bengaluru Metropolitan Transport Corporation from Government of Karnataka and clustered according to the distance travelled over different routes as shown in Fig 2.

TABLE 1. SAMPLE DATA OF BMTC CRASH REPORT

Location	Date/Timing	Route	Event Type
MG Road	2018-02-01T01:48:59.000Z	G-1	Over Speed
Borewell	2018-07-05T01:55:38.000Z	WFS-1	Over Speed
Brigade Road	2018-07-09T02:05:43.000Z	G-4	UFCW
Vasanthapura	2018-03-21T02:26:46.000Z	FDR-2	PCW

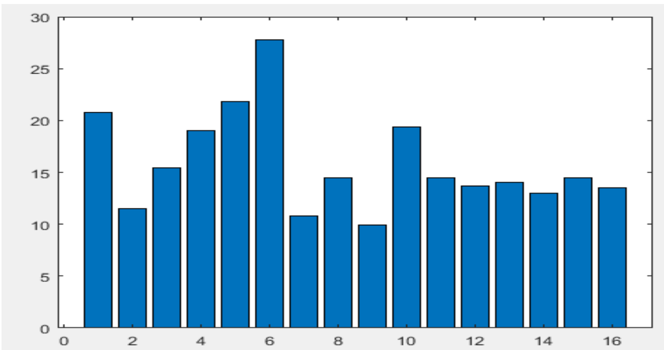

Fig.2. Prediction trade off measure between distance travels over different path routes

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CNN model: Here statistical measures are obtained by using a CNN which is empowered to learn the relationship among the individual data sets with some finite discrimination and exploration. A convolutional neural network is consists of several convolutional layers with appropriate activation functions and parameters as follows:

$$\mathbb{Q} = \{w, B\} \qquad \text{eq. (1)}$$

Where w is a set of convolution kernels, and B is a bias.

At each layer, the input I is convolved N numbers of kernels $w = \{w_1, w_2,\ldots,w_N\}$ and associated biases $B = \{B_1, B_2, \ldots, B_N\}$. During the convolution operation, a new feature map I_{mid} is generated at each layer. An activation function is formulated from each of these feature maps to carry out non-linear transform over the input. The process is involved in each layer is formulated by using Eq. (2) as shown below:

$$IkCL= g(w * IkCL\text{-}11) \qquad \text{eq. (2)}$$

Where here, '*' the convolution operation and g denote the activation function, CL refers to the total number of the convolutional layers in the CNN network.

Here input data information values are decomposed into several groups of details and based on its spatial correlation and its variations mapping functions are formulated as given below:

//Input – BMTC data
//Output – Prediction (Timing - Location)
Step 1: Data pre-processing to extract location and associate timing of accidents
Step 2: Set activation function and formulate non-linear transform
Step 3: Apply performance analysis model over-prediction output

B. *Experiments and Results:*

The performance metric evaluation of the proposed framework has experimented over the data collected from the URL https://mybmtc.karnataka.gov.in dataset, which is public transportation set. This dataset contains all bus details with relevant accident information. To train the CNN model, each set is divided into different sets for the training phase and for test validation. The performance penalty gap between actual classes and predicted value bounds are narrowed down using the appropriate training set as shown in Fig 3.

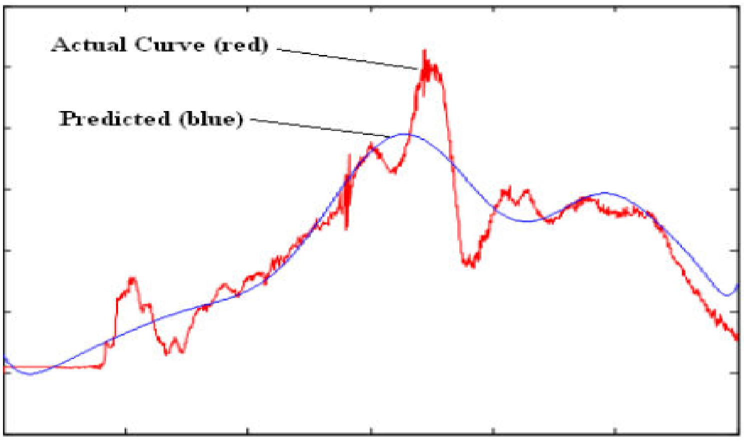

Fig.3. Time of incidents vs. cases prediction model

C. *Performance analyses:*

To speed up the prediction measurement, it is essential to improve the quality of the learning model and restore all particular. To accomplish this task learning model using CNN with three hidden layers and carried out detailed feature extraction for the Different Prediction Measures As shown In Fig 4 and 5. The Analyses Includes Classification of Different Accident Causes Namely Overspeed, Forward Collision, Pedestrian Collision, Urban Forward Collision, Lane Departure, and Headway Monitoring over a period of time as shown in Fig 6. In DL-based approaches input, big data is

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processed at the low space and allows only superior and potentially useful measures like location, time of incidents, and frequency of occurrences. Here the accumulation of convolution layer and other network substitution within the hidden layers are prominently decided the overall prediction quality and convergence rate as well. This DL framework over input measurements not only offers improved quality also helps the most appropriate examination of accidents as it allows superior results over different causes of accidents over public transportation systems.

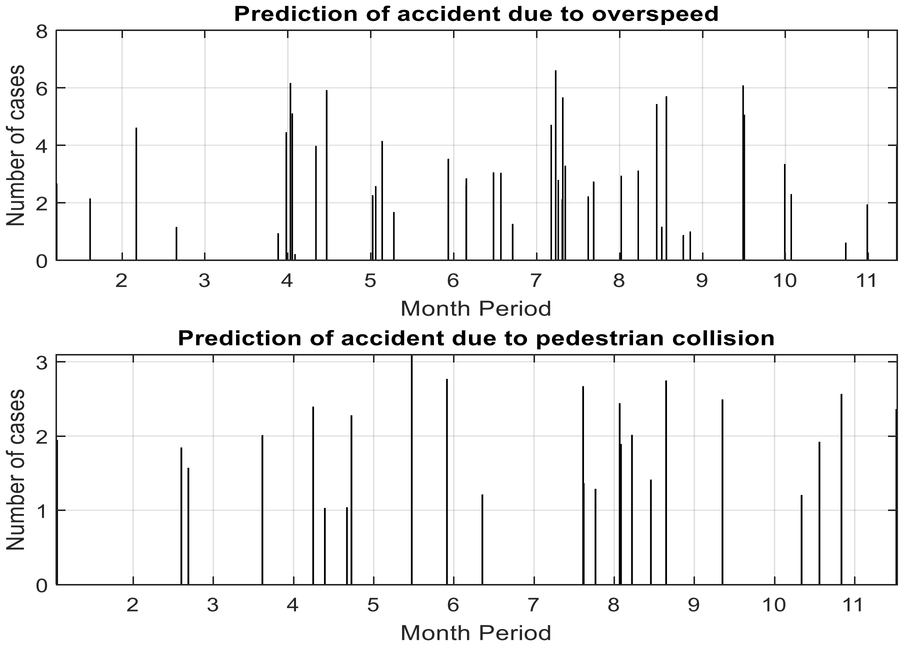

Fig. 4. Accident prediction due to two different major causes

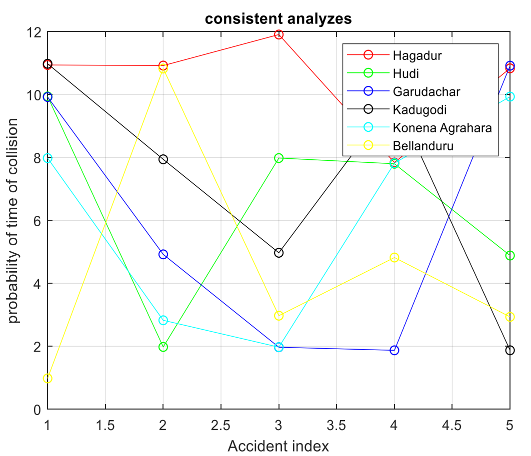

Fig. 5. Time bound probability measure over different locality

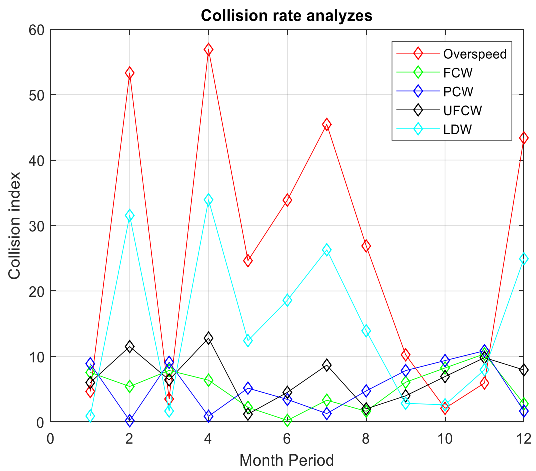

Fig. 6. Time index vs. Collision reason

V. CONCLUSION AND FUTURE WORK

This work presents a deep learning approach to maximize the prediction accuracy of public transport accidents and its relevance exploration. The proposed estimator model aims to incorporate maximum details from subsequent years and associated data interpretation as a preceding layer which gives most linear statistical measurements; By estimating the correlation between the different data extracted from two different years and its relations to estimation performance are generalized using multi-layered residual block driven training phase. We presented the methodology of emergent intelligence in this research work for traffic management in a metropolitan area based on prediction data. The inputs for the suggested methodology as well as for the prediction model were traffic flow parameters such as speed, density, past information, as well as spatiotemporal correlated information. The suggested model minimized the frequency of traffic congestion, traffic density expansion, as well as traffic flow in every area as well as city at different intervals throughout the day. In areas as well as zones, the EI methodology successfully obtained, evaluated, distributed, as well as estimated traffic densities as well as traffic flow time. Therefore, to prevent unnecessary variation as well as non-linearity of traffic systems, this research work exhibits the properties of autonomy, adaptability, flexibility, robustness, as well as self-organization. We evaluate the proposed model by comparing the characteristics as well as competencies of EI as well as SI methodologies for traffic management in urban areas. In contrast to other conventional techniques such as CNN, ANN, as well as SVM, the proposed prediction method has been thoroughly analysed. The simulation results demonstrate that the methodology of EI outperformed the swarm intelligence technique in terms of traffic management by effectively handling traffic to minimize the time taken to make reliable decisions and to minimize computation complexity.

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