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ADVANCING TRAFFIC SAFETY THROUGH CAPRNN: A HYBRID CAPSULE-RECURRENT NEURAL NETWORK FOR ACCIDENT FORECASTING

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ABSTRACT

One of the primary causes of death globally has been traffic accidents involving vehicles on public roads. To address this issue, we introduce Capsule Recurrent Neural Network (CapRNN), a new deep learning architecture designed specifically to improve road accident prediction performance. CapRNN uses capsule networks for capturing spatial relationships and recurrent neural networks for capturing temporal patterns. A series of experiments has been performed with CapRNN on a large-scale dataset of U.S. traffic accidents from 2016 to 2023 and compared it with other typical models. The result was the 95.82% accuracy of CapRNN, which was the highest one. The standard LSTM and Bi-LSTM models could only achieve 93.58%, respectively. Also, the performance of CapRNN was higher than that of XGBoost (95.73%) and Random Forest (95.02%). Besides accuracy, recall was also high for CapRNN (95.82%) and precision was also high (95.24%), i.e., it was stable at different time resolutions. This finding supports our claim that hybrid deep learning models like ours have the potential to effectively solve the spatiotemporal nature problem of road accident data. CapRNN's improved prediction accuracy could be used directly to make public safety policies more efficient by enabling them to better allocate the resources devoted to traffic management and urban planning. We, therefore, propose further steps: testing the model on other data sets, making it more interpretable, and, finally, incorporating real-time data to strengthen predictions.

KEYWORDS

Capsule Recurrent Neural Network (CapRNN), road accident prediction, deep learning, accident forecasting, capsule networks.

1. INTRODUCTION

Road traffic crashes are still among the major causes of global ill health, resulting in many deaths, huge financial burdens, personal suffering, and economic losses worldwide (World Health Organization). The accurate prediction of accidents can be helpful for the development of effective prevention policies and the enhancement of road safety. During the last decade, the research community has introduced several machine-learning techniques to tackle this issue, varying from traditional statistical methods to entirely different approaches such as neural networks and ensemble models. However, there is still some issues left in terms of the models' accuracy and robustness, especially when it comes to their capability to reflect the complex spatiotemporal dynamics of road accidents.

In recent works, authors have pointed out the most crucial factors that can heavily influence the occurrence of accidents. The most notable freight vehicle drivers' situations have been the primary causes of road crashes. Built on this, (Asad & Saeed, 2024) analyzed that the rate of accidents is less among educated drivers (high school or intermediate school) than among the illiterate ones. As per this research analysis, driver education and training programs might play an essential role in the reduction of truck accidents. It is a level of education that plays vital role in accident prevention, but behavioral factors still have a major influence on road safety.

(Asad & Hadi, 2024) analyzed that the use of a mobile phone while driving is an alarmingly frequently case, mainly among the youth and male drivers, and there is clear evidence of the absolute link between such behavior and the increased chances of accidents.

This study presents the Capsule Recurrent Neural Network (CapRNN), a deep learning model that combines the advantages of capsule networks in detecting spatial hierarchies and relationships with the sequential data processing capabilities of recurrent neural networks. By integrating these elements, CapRNN aims to model complex patterns in road accident data. Which helps to understand how factors like weather, traffic, and road conditions influence accident risks over time and across locations.

The contributions of this paper are:

1. The CapRNN model combines capsule routing with a recurrent neural network for predicting accidents. This allows for analysis of spatial and temporal data, improving both prediction accuracy and context.

2. A series of tests has been conducted to compare CapRNN to the most competitive baseline models. These tests use a variety of real-world accident data collected from different scenarios, regions, and time periods to confirm the model's reliability and practicality.

3. By exploring the model's interpretable features, we identify the key factors that most significantly cause accident risk. The clarity of CapRNN through capsule networks highlights feature importance and interactions, supporting a focused safety strategy.
4. Evidence shows that CapRNN has superior predictive power and can generalize better than existing methods. The thorough data analysis demonstrates CapRNN's clear advantage across various performance metrics.

First, the results of this research concern both the academic community and the public. One immediate outcome of this project could be its positive effect on public safety policies and resource allocation. As the accuracy and reliability of road accident predictions improve, traffic management can become more efficient. Authorities can pinpoint high-risk areas through model predictions and take preventive measures, thereby reducing the number of accidents. Additionally, urban planners could use this information to design safer and more efficient transportation systems. The paper reviews the development of accident prediction methods, moving from traditional statistical models to machine learning algorithms. By highlighting the limitations of these methods, it positions CapRNN as a viable new alternative.

This article describes the CapRNN model with its scientific underpinning, its structural units, its training process, the devices for running the experiment, a description of the data, the preparation of the data, and the evaluation process. After this the article presents the research results with a descriptive account with evaluation of the results and their immediate and potential use of the study. Finally, the research will summarize the main contributions to the field of public safety along with its limitations and future research directions.

2. RELATED WORKS

RNNs have been widely used in a variety of fields of prediction, such as software reliability (Bhuyan et al., 2016), network traffic (J. Fan et al., 2019), and road traffic (Kim et al., 2019). Although the old RNNs have also been effective, the scholars have gone on to create new and specialized versions of the RNN to curb certain challenges in various areas. RNNs have also been popularly used as feature extractors for different prediction tasks.

In the framework of network security, researchers have proposed novel RNN models to enhance prediction capacity. To predict network-security situations, the Clockwork Recurrent Neural Network (CW-RNN) has been suggested to represent both long and short-term temporal dynamics and nonlinearity (Du et al., 2023); this model is better on prediction and real-time prediction.

Beyond network security, RNNs have been implemented to predict energy issues including wind-power prediction, within renewable energy. Here, a better cyclic neural network model, which is grounded on variational modal decomposition (VMD), has been created (Shi & Zhang, 2023). VMD method is used to break down wind-power output into various frequency components and the features that are derived are then fed to a neural network to improve real-time predictive performance.

Time-series Recurrent Neural Network (TRNN) has been suggested in the world of financial projections (Lu & Xu, 2024). The TRNN uses sliding-windows on time-series data, which are extracted into trends and turning-points, based on financial-market characteristics, and hence prove to be more efficient and accurate compared to conventional RNNs and LSTMs.

In addition to prediction, RNNs have been modified to be used in complex system anomaly detection. Having two parallel ConvLSTM flows, (Sivalingan, 2024) can pay attention to important details of the data, thus providing strong and timely anomaly detection.

Also, RNNs have been combined with other neural-network models to solve spatial-temporal problems, e.g., remote-sensing image classification. An unusual hierarchical convolutional recurrent neural network (HCRNN) has also been created (Fan et al., 2023); it integrates CNN and RNN into its structure and is able to recognize time and space-varying features of spectral data, thus providing high-precision pixel-wise classification of multispectral images. In all of these wide-ranging applications, such as network security to remote sensing, the papers show the efficacy of RNNs in identifying temporal patterns and providing correct predictions. A systematic review on road accident prediction is discussed in detail in (Verma & Agarwal, June 2025)

Methods based on neural networks have been successful in discovering those factors that cause road-accidents occurrence and predict their severity (Shaik et al., 2021). Some of the available neural-network architectures that researchers have applied to this end include single-layer perceptions (SLP), multilayer perception (MLP), radial-basis-function (RBF) networks, and more complex architectures like RNNs and convolutional neural networks (CNNs). High precision and efficiency in predicting road accidents have been achieved through the use of these advanced learning techniques especially RNNs and CNNs.

Some research has also been done on hybrid architectures that mix two or more types of neural networks. As an illustration, a framework that combines deep RNN and gated-recurrent unit (GRU) has been offered to predict network-traffic (J. Fan et al., 2019). Another hybrid scheme, the Quasi-Recurrent Neural Network (QRNN) combines the benefits of RNN and CNN and has been introduced to predict short-term loads in power systems (C. Yang et al., 2021), Another hybrid scheme, the Quasi-Recurrent Neural Network (QRNN) combines the benefits of RNN and CNN and has been introduced to predict short-term loads in power systems.

Based on these hybrid solutions and the need to have more advanced models when it comes to predicting traffic, offer a new solutions by presents a novel improved focal-loss operation (Verma & Agarwal, 2024, Verma & Agarwal, 2025) which includes adaptive weighting procedures, time-dependent data, spatial context, multiscale learning and uncertainty-sensitive formulation. Another novel approach combining genetic algorithm-based feature selection and enhanced focal loss to improve traffic accident severity prediction (Verma & Agarwal, March 2025). ACEFIT addresses key model limitations and achieves up to 96.71% accuracy, outperforming existing methods on the US Accident dataset. The purpose of these approaches is to address the shortcomings of the current models that have difficulties with the balance of classes and lack the ability to incorporate real-time traffic and weather data.

Similar innovations strategies are also implemented to the similar fields, like the object detection in the low-visibility conditions, as researchers perfect the models of traffic-prediction. A new method, which is demonstrated in (Sain et al., 2024) to enhance the performance of object-detection in foggy weather, is termed, Clear Detect, a blend of image-dehazing and advanced object-detection algorithms, thus alleviating accidents that are caused by non-homogenous dense fog during surveillance systems.

Structural RNNs (SRNNs) have also shown potential in jointly using road-network topology when learning the network (Kim et al., 2019). The methodology has yielded better results than the image-based approaches that utilize capsule networks (CapsNets) and CNN. Specifically, the scalability of SRNNs that allow making predictions on different road systems with fixed parameters is also remarkable.

Even though this study is not directly related to road-accidents prediction, studies in other areas have provided insights on the relative performance of RNN architectures. As an example, Gated Recurrent Unit (GRU) was more effective than typical RNN and Long Short-Term Memory (LSTM) networks in long-term stock-market prediction (Kalbaliyev & Szegedi, 2021). On the other hand, LSTMs have smaller predictive errors on short-term predictions of traffic-flow than GRUs and stacked autoencoders (SAEs) (Kim et al., 2019). Even though these studies dealt with a variety of applications, they are valuable insights into the ability and limitations of various RNN structures that can be used to predict road-accidents.

Such recent trends in road-traffic-state prediction have highlighted the effectiveness of different neural-network designs. GERNN, which uses road networks as graphs, has demonstrated the potential to solve complex traffic systems by more effectively modeling spatiotemporal traffic-flow features. Another important technique is the spatiotemporal attention -gated recurrent neural network (ST -AGRNN); the technique synthesizes spatial information obtained with graph structure and location through graph convolutional networks and DeepWalk, and it adds attention mechanisms to identify global spatiotemporal patterns (Yang et al., 2022).

A framework for road accident prediction in India using Enhanced Support Vector Machine (SVM) techniques developed to addressing challenges such as class imbalance, high-dimensional data, and non-linear relationships, this research improves upon traditional SVM models (Agarwal et al., 2025). The proposed model utilizes feature engineering, kernel tuning, and hybrid approaches to provide accurate accident predictions. Using real-world accident data from Indian roads, the enhanced SVM framework demonstrates superior performance compared to traditional models, offering a robust tool for policymakers and traffic management authorities.

Prediction of road accidents has shown the tendency to combine various sources of data and advanced neural-network structure. Attention Based Dynamic Graph Convolutional Recurrent Neural Network (ADGCRNN) is a state-of-the-art model, which can overcome the difficulties of maintaining spatiotemporal coherence in long-duration predictions (Zhang et al., 2023). The ADGCRNN has shown superior performance using multi-dynamic graphs, self-attention and specialized gated kernels which has enabled the prediction of traffic flow and as such the ADGCRNN has the potential to provide greater capabilities of road accident prediction.

All these diverse applications and discoveries highlight the possibility of recurrent neural networks (RNNs) and their derivatives in prediction problems, such as road accidents. The proposed Capsule Recurrent Neural Network (CapRNN) prediction of road accidents is based on the broad set of research, which may combine the benefits of capsule networks with RNNs to achieve higher levels of accuracy in prediction and the ability to identify complex spatiotemporal behavior of road accidents.

3. RESEARCH GAPS

RNNs, CNNs, and hybrid neural network models are used widely to predict accidents, but they cannot handle both spatial and temporal dimensions. In a nutshell, current techniques generally treat spatial relationships, e.g., CNNs or Capsule Networks, and time patterns, e.g., RNNs or LSTMs, separately. Consequently, they seldom recognize propagation of spatial and temporal aspects at the same time. As an example, Structure RNNs might be competent to integrate the road network structure, yet they are probably not complete in capturing intricate spatial hierarchies and relations that result in accidents. Besides, the accountability of the systems based on deep learning is still a very difficult task, which, in turn, makes their deployment for the precisely targeted safety application unlikely. Capsule Recurrent Neural Network (CapRNN) introduced by the paper intends to close these distances by combining capsule network-based spatial modeling with RNNs-based temporal sequence modeling. This method can help to accurately predict road accidents and interpret the model.

4. METHODOLOGY

In the current study, a deep learning architecture, Capsule Recurrent Neural Network (CapRNN), is proposed to predict vehicle crashes. CapRNN is a combination of capsule network and a recurrent neural network that combines spatial and temporal features of accident data. The model had been tested using empirical information obtained at different geographical positions and periods. Its ranking of performance was determined using comparative analysis with other models, based on its ratio like accuracy and generalizability.

The paper also outlines the way CapRNN determines spatial and temporal determinants that lead to accidents. The architecture gets a higher predictive accuracy by exploiting the spatial relational benefits of capsule networks and the temporal representational benefits of recurrent neural networks and provides more insight on safety advisability.

4.1. Data Collection

The paper also outlines the way CapRNN determines spatial and temporal determinants that lead to accidents. The architecture gets a higher predictive accuracy by exploiting the spatial relational benefits of capsule networks and the temporal representational benefits of recurrent neural networks and provides more insight on safety advisability.

4.2. Dataset Description

The dataset contains all the necessary variables needed to understand and predict accidents, such as a unique identifier of an accident, the origin of the report, level of severity, and spatial area (in miles), as well as signs of traffic control measures, like turning loops or signals. Moreover, time markers such as the Sunrise/Sunset, Civil Twilight, Nautical Twilight, and Astronomical Twilight allow studying any incidents that happened at different periods of the day. This concise introduction gives the attributes of data that make it easy to scrutinize and model the incident information rigorously, thus helping to design the roadways more safely and prevent accidents.

4.3. Data Pre-processing

Data preprocessing is an important step in preparing raw data for analysis and modeling. It involves cleaning, transforming, and organizing data to improve quality for machine-learning algorithms. Key activities include handling missing values, removing duplicates, converting categorical variables, adjusting numerical features, and managing outliers. Data may be normalized or standardized to achieve consistent feature scaling. Techniques like PCA reduce the number of features by simplifying dimensions. The dataset is also split into training and test sets. Good preprocessing minimizes noise and inconsistencies. This leads to more accurate and reliable models, making it vital for data analysis and machine learning.

4.3.1. Data Cleaning

The dataset contains all the necessary variables needed to understand and predict accidents, such as a unique identifier of an accident, the origin of the report, level of severity, and spatial area (in miles), as well as signs of traffic control measures, like turning loops or signals. Moreover, time markers such as the Sunrise/Sunset, Civil Twilight, Nautical Twilight, and Astronomical Twilight allow studying any incidents that happened at different periods of the day. This concise introduction gives the attributes of data that make it easy to scrutinize and model the incident information rigorously, thus helping to design the roadways more safely and prevent accidents.

4.3.2. Feature Engineering

The data screening phase involved checking the dataset regarding missing values. Columns with extreme omissions were eliminated to maintain high quality of data. The date-time data was divided into constituent elements, such as year, month, day, hour, and minute, to provide clarity in the analysis. The coding of the work to binary (1- True and 0- False) was performed, which simplified the incorporation of the fields and their inclusion in machine-learning processes to train and evaluate the models.

4.3.3. Low variance Techniques

Low-variance columns were identified and removed to simplify the dataset by removing extra features with the help of a systematic process. This dimensionality compression technique improves computational performance, and it also improves the performance of the model. The refined data is more focused on informative variables that have significant variation; hence, making the process of analysis more focused.

4.4. Train-Test Split

The data were divided into the traditional train test split method that provided separate training and test sets. This is the protocol that made sure that there was no biased assessment of model generalizability on unseen data. Model development was done with the training subset, and the testing subset was used as an independent validation set to test the ability of the model to generalize.

4.5. Model Building and Training

Trained prediction models based on Recurrent Neural Networks (RNNs) and Capsule Networks (CapsNets) to predict the severity of accidents. RNN architecture was chosen due to its ability to work with sequential data and identify trends of traffic over time. The reason why CapsNets have been included is their ability to maintain spatial association and to encode features in a hierarchical manner. The combination of these architectures was to utilize the complementary strengths and consequently increase the predictive performance of the models.

4.5.1. CapRNN Architecture

CapRNN involves data processing of road accidents through the combination of capsule networks and recurrent neural networks. This spatiotemporal model summarizes the spatial (location based) and the time (temporal) factors of crash information, giving a holistic picture of the factors that affect the safety of roads. Fig. 1 depicts the CapRNN architecture, which consists of several key elements that the system is based on and the functionality and effectiveness.

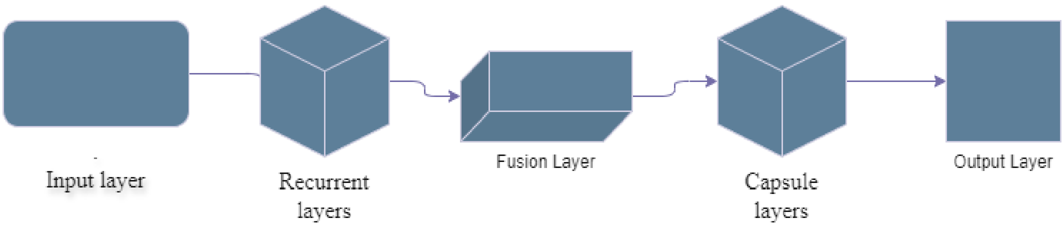

Fig.1 Block diagram of the CapRNN

1. Input layer: This initial stage processes raw accident data. It includes spatial elements like geographic coordinates, street classifications, and surrounding conditions. It also covers temporal information such as hours, weekdays, and seasonal variations. This stage gets these different features ready for further processing by the next layers.

$$X \in R^{T \times 1} \quad (1)$$

where T is the length of the input sequence.

2. Capsule layers: Integral to the CapRNN architecture, and based on capsule network theory, these layers extract spatial hierarchies and feature relationships through dynamic routing between capsules. This method keeps important spatial information about accident factors. It includes the positions of vehicles, pedestrians, and road features, preserving the complex spatial relationships that traditional convolutional neural networks often miss.

$$P = Reshape(Dense(D_4, units = f), [-1, c]) \quad (2)$$

where f is the number of filters, and c is the dimension of the capsules.

$$U = P \cdot W \tag{3}$$

$$U \in R^{N \times d} \tag{4}$$

where N is the number of capsules, and d is the dimension of each capsule.

$$V = squash(\sum_{i=1}^{N} U_i) \tag{5}$$

3. Recurrent layers: The CapRNN model uses recurrent layers of LSTM or GRU cells to model the time aspect of accident data. These are cells that are meant to model and capture sequential dependencies. Through the data being processed as a time series, the model determines the changing patterns and trends, such as daily traffic patterns, weekly patterns, and long-term accident trends. Fig. 2 shows the overall scheme of a recurrent neural network (RNN).

$$H_t = GRU(X_t, H_{t-1}) \tag{6}$$

$$H \in R^{T \times r} \tag{7}$$

where 'r' is the number of RNN units.

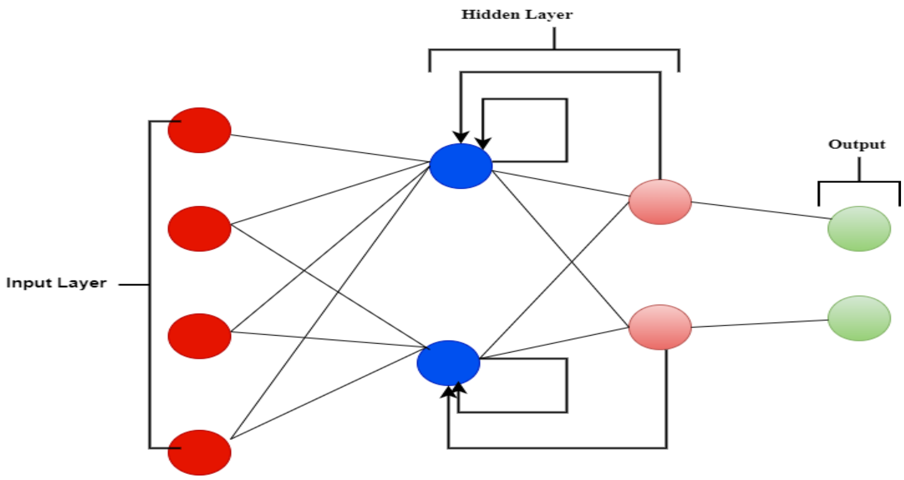

Fig.2 Recurrent neural network architecture

4. Fusion layer: This is a critical part of the CapRNN network, as the fusion layer combines the capsule and recurrent network outputs. It combines spatial representations produced by the capsule layers with temporal patterns produced by the recurrent layers and, as a result, results in the creation of a unitary representation that captures spatial as well as temporal features of data related to accidents.

5. Output layer: This is a critical part of the CapRNN network, as the fusion layer combines the capsule and recurrent network outputs. It combines spatial representations produced by the capsule layers with temporal patterns produced by the recurrent layers and, as a result, results in the creation of a unitary representation that captures spatial as well as temporal features of data related to accidents.

$$O = Dense(G, units = 4,\ activation = softmax) \tag{8}$$

CapRNN architecture has been defined as the one in which there is the bidirectional flow of information between the capsule and the recurrent modules. In this design, dynamic cooperation between spatial and temporal data features is allowed; capsule layers make spatial regularities known to temporal analysis on the recurrent layers and vice versa. Therefore, the model considers spatial interactions and time trends in estimations.

The use of dynamic routing in capsule layers is beneficial to analyzing road accident data because it separates sets of salient features that could indicate high-risk conditions such as sharp turns, wet roads and peak-hour traffic. The sequential layers represent short term and long-term evolution of these combinations of features and risks.

CapRNN model has multiple advantages: the model itself is very successful in being more representative of the deep data of road accidents due to its ability to use capsule network and recurrent neural network technologies:

1) Improved prediction accuracy: The process of combining both spatial and time elements strengthens accuracy in prediction of accidents and prediction of the severity of the accidents.

2) Greater understanding of the determinants of risk: The discovery of the interaction between the complex features reveals new risk factors.

3) Temporal trend analysis: Recurrent components allow analyzing the development of accident patterns in detail over time, which is helpful in long-term planning and policy making.

4) Identification of the spatial patterns: Capsule layers can maintain spatial hierarchies and can be used to identify hazardous areas or road features that increase the risk.

5) Flexibility: The architecture can be adjusted to the different road safety data sets and adjusted to different geographic and urban settings.

Capsule and recurrent neural networks together in the CapRNN architecture provide a solid solution to the problem of the interrelations in traffic accidents data, which is complex to address, but can enable more effective road safety interventions and reduce the number of collisions.

4.5.2. Model Development

CapRNN design combines the ability of capsule neural networks with recurrent neural networks to deal with complex data about accidents, and to coordinate spatial and temporal input using the coupled layers. The first layer has 128 units to support multi-dimensional accident data. Capsule layers make use of dynamic routing schemes to release spatial hierarchies. There are three major layers of capsule configuration, that is 32, 64, and 128 capsules with 16 neurons each. GRU cells are used to capture the temporal dependencies in recurrent layers, which are augmented by 256 two-way units of LSTM to provide the full analysis of the time. Outputs are then combined in a single spatiotemporal representation in a fusion layer of 512 neurons which is then densely transformed. Two more thick layers of 128 and 256 neurons respectively have ReLU activation. The classes or risk categories that require prediction are defined by the output layer which comprises one to ten neurons. Detailed rigidity is extremely important at development stage, as it includes input preprocessing, fusion, and output configuration. Complicated trends in accidents are reflected in the model, due to mutual flow of information, which allowed interaction between space and time. Training processes entail backpropagation of recurrent elements and dynamic routing of element components of a cap. Basic hyperparameter refinement, which is coupled with validation on an independent test dataset is necessary to obtain the best performance and guarantee generalization. This method will be used to build a powerful model that is able to effectively incorporate both spatial and temporal dimensions of data in the occurrence of accidents, thus allowing good risk assessment and prediction in real world scenarios.

4.5.3. Model Evaluation

It was found that the performance of the strategy was assessed using the metrics based on the confusion matrix, such as the accuracy, the sensitivity, the precision, and the F1-score. A confusion matrix is a statistical tool used to compare the predicted classifications with the true labels in the dataset to evaluate the performance. It also splits predictions into true positives, true negatives, false positives, and false negatives hence providing an extended perspective of the accuracy, as well as the effectiveness. The categories allow estimating a series of performance indicators. Evaluation measures have been presented as different measures that give an understanding of the strengths and weaknesses of a model. As an example, high accuracy does not always imply effectiveness in case of unbalanced distributions in the classes. A model can be highly sensitive and low in precision, which implies that it is prone to false positives. When these measures are interpreted together, researchers can have a more realistic insight into the practical performance of a model and choose the most appropriate approach to perform a certain classification task.

Accuracy: This measure is determined by dividing the number of the correct instances mentioned by the total number of instances.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

Sensitivity: This statistic measures the percentage of correct positives that the model makes. This is the ratio of true positives to all the positive examples.

$$Sensitivity = \frac{TP}{TP+FN} \quad (10)$$

Precision: The precision gives the percentage of the number of predicted positives which are truly positive and is defined as the number of true positives divided by the total number of false positives and the number of true positives.

$$Precision = \frac{TP}{TP+FP} \quad (11)$$

F1-score: This is a harmonic mean of precision and sensitivity that integrates both measures into a single figure balancing the trade-offs between these two measures.

$$F1 - score = 2 * \frac{Precision*call}{Precision+call} \quad (12)$$

Specificity: Specificity is an important measure that shows how well a model correctly identifies negative cases.

$$Specificity = \frac{TN}{TN+FP} \quad (13)$$

Geometric Mean (GEO): This measure evaluates the engine of model that captures the rate of true negative information that is recognized properly by the model; it is expressed as the division of actual negative cases by the overall quantity of nervous cases.

$$GEO = \sqrt{(TPR \times TNR)} \quad (14)$$

Index of Balanced Accuracy (IBA): This is the measure of the effectiveness of a classification model that considers sensitivity and specificity at the same time, thus measuring the capability of a classification model to sort the data into the correct category.

$$IBA = (TPR + TNR)/2 \quad (15)$$

5. RESULTS

CapRNN model outperformed the baseline models and had a precision of 95.82% in general road accidents as indicated in Table 1. The values of the confusion matrix showed that the model had a recall rate of 95.82% implying that the model has the ability of identifying true-positive cases with high level of accuracy. Its specificity was 95.24%, which showed successful repression of false positives. The F1-score which measures precision and recall was 94.93% giving the strength of the model.

Table 1. Performance Metrics

Model	Accuracy	F1-score	Precision	Recall	Specificity	GEO	IBA
CapRNN	95.82%	94.93%	95.24%	95.82%	49.75%	67.51%	47.95%
LSTM	93.58%	90.48%	87.57%	93.58%	46.41%	62.46%	46.10%
Bi-LSTM	93.58%	90.48%	87.57%	93.58%	46.41%	62.46%	46.10%
XGB	95.73%	94.77%	95.19%	95.73%	45.88%	64.51%	43.91%
Random Forest	95.02%	93.35%	94.64%	95.02%	29.47%	49.28%	26.13%

Its specificity was 49.75%, which is a good result of the ability to detect negative results and prevent false alarms in accident prediction systems. The geometric mean (GEO) was 67.51%, which showed that there was a balanced performance between the classes and that imbalanced datasets were well managed. The Index of Balanced Accuracy (IBA) at 47.95% was confirmed and this proved the model to be operating effectively on various types of accidents and road conditions.

There are various notable gains compared to baseline models achieved by the CapRNN Fig. 3. Traditional LSTM and Bi-LSTM models were able to reach an approximation of 93.58%., whereas the XGB was 95.73% and random forest (RF) 95.02%. By comparison, CapRNN secured the accuracy of 95.82%, which was a significant improvement. Besides, CapRNN also exhibited scalability as the highest drop in accuracy up to generating long-term predictions concerning one month.

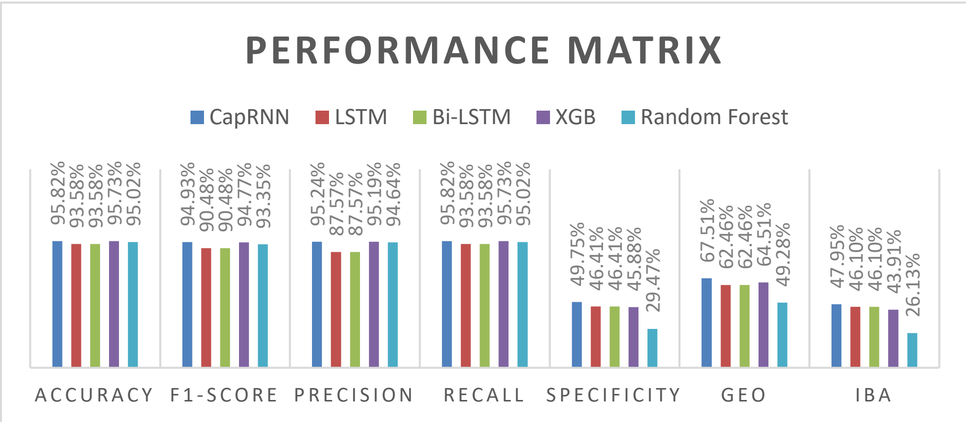

Fig.3 Performance Metrics

These findings mean that CapRNN is an improved accident prediction model because it incorporates spatial and temporal patterns in accident data, which has an advantage over the conventional LSTM and Bi-LSTM, XGB, and RF baselines in terms of predictive accuracy and generalization. The ability of the model to exploit spatial dependencies by using its capsule network architecture coupled with robust temporal modelling is behind the model super performance.

6. DISCUSSION

The suggested Capsule Recurrent Neural Network (CapRNN) is better in predicting road accidents than the usual procedures. It achieves an accuracy of 95.82%, which is higher than the baseline LSTM models and Bi-LSTM models that had an accuracy of 93.58%. The XGB model obtained 95.73%, and the Random Forest (RF) model also obtained 95.0%. The recall (95.82) and measured the level of precision (95.24%) values are high, which indicates that the model has great qualities in identifying accident risks and it minimizes the number of false positives. A balance of performance is supported by F1-score of 94.93%. The model has a desirable robustness to imbalanced data also present in real-life data prediction problems in accident prediction; this also highlights that the predictor model can be used to determine and predict events that are critical yet rare not subjugated by the more common non-accidents.

7. CONCLUSION

This paper shows a deep-learning model, the Capsule Recurrent Neural Network (CapRNN), which has been created to support road-accident prediction better. CapRNN made an accuracy of 95.82% tempers better compared to base line LSTM and Bi-LSTM (93.58% and 95.02% respectively) and XGB (95.73%) and random forest (95.02%) outcomes.

Key findings include:

1) CapRNN had a high recall (95.82%) and accuracy (95.24%) that showed the effectiveness in detecting risks of accidents, and the reduction of false positives.

2) The model was stable at short time scale; its accuracy was lower when the model was used as a long-period prediction.

3) CapRNN was able to learn both spatial and temporal patterns of the accident data by introducing the use of capsule networks and recurrent neural networks.

These findings underscore the distinctiveness of CapRNN in complex spatial and temporal features applicable to road-accident predictions albeit with more accurate and context specific road-accident predictions, in comparison with the current dexterities. Outside the academic outcomes, the greater accuracy and reliability of CapRNN might have an impact on safety policy and resource allocation. Traffic officials can use its knowledge to set anti preventive controls that were found to be dangerous, whilst urban planners might utilize the information to build infrastructure.

Weaknesses of the research are:

1) Generalizability: The model was not evaluated directly on different datasets in different locations or in different conditions, assessing the model on multiple datasets would prove the assertions of generalizability.

2) Interpretability: As much as the paper addresses the need to have a model that is quickly interpretable, it does not avail clear information on how predictions are formed and which factors have a more tremendous impact, hence restricting practical recommendations to the policy and planner.

3) Data sources: The analysis uses only historical accident data and does not incorporate real-time information data, even the current traffic conditions or weather predictions, which may provide additional predictive accuracy.

To optimize practical uses, future studies need to:

1) Assess the model using different data sets in different areas to verify the generalizability.
2) Improve interpretability to deliver actionable information to the stakeholders.
3) Combine other real-time sources of data to increase the accuracy of predictions.

Overcoming these shortcomings would also enhance the role played by CapRNN in road safety and traffic control. Overall, the CapRNN model takes huge steps forward in road accident prediction and proves the capability of the hybrid deep-learning systems to handle the complex real-world problems and finally, decrease the number of road accidents and enhance the level of community safety.

8. REFERENCES

Agarwal, M. M., Verma, R., & Berwal, K. (2025, May). Building the Framework for Road Accident Prediction for India using Enhanced SVM Techniques. In 2025 IEEE International Conference on Computer, Electronics, Electrical Engineering & their Applications (IC2E3) (pp. 1-6). IEEE.

Asad, F., & Hadi, S. (2024). Modelling The Factors Affecting Crash Occurrence and Frequency Resulted From Mobile Phone Use While Driving: Evidence From Al-Najaf, Iraq. Kufa Journal of Engineering, 15(2), 74–92. https://doi.org/10.30572/2018/KJE/150206

Asad, F., & Saeed, M. (2024). Investigating The Risk Factors Affecting The Occurrence, Frequency, And Severity Of Large Truck Accidents In Al-Najaf Governorate, Iraq. Kufa Journal of Engineering, 15(1), 30–46. https://doi.org/10.30572/2018/KJE/150103

Bhuyan, M. K., Mohapatra, D. P., & Sethi, S. (2016). Prediction Strategy for Software Reliability Based on Recurrent Neural Network (pp. 295–303). https://doi.org/10.1007/978-81-322-2731-1_27

Du, X., Ding, X., & Tao, F. (2023). Network Security Situation Prediction Based on Optimized Clock-Cycle Recurrent Neural Network for Sensor-Enabled Networks. Sensors, 23(13), 6087. https://doi.org/10.3390/s23136087

Fan, J., Mu, D., & Liu, Y. (2019). Research on Network Traffic Prediction Model Based on Neural Network. 2019 2nd International Conference on Information Systems and Computer Aided Education (ICISCAE), 554–557. https://doi.org/10.1109/ICISCAE48440.2019.221694

Fan, X., Chen, L., Xu, X., Yan, C., Fan, J., & Li, X. (2023). Land Cover Classification of Remote Sensing Images Based on Hierarchical Convolutional Recurrent Neural Network. Forests, 14(9), 1881. https://doi.org/10.3390/f14091881

Kalbaliyev, E., & Szegedi, G. (2021). Long Term Stock Market Prediction with Recurrent Neural Network Architectures (pp. 1084–1093). https://doi.org/10.1007/978-3-030-71187-0_100

Kim, Y., Wang, P., & Mihaylova, L. (2019). Scalable Learning With a Structural Recurrent Neural Network for Short-Term Traffic Prediction. IEEE Sensors Journal, 19(23), 11359–11366. https://doi.org/10.1109/JSEN.2019.2933823

Lu, M., & Xu, X. (2024). TRNN: An efficient time-series recurrent neural network for stock price prediction. Information Sciences, 657, 119951. https://doi.org/10.1016/j.ins.2023.119951

Sain, S. K., Khandelwal, K., & Agarwal, M. M. (2024). Smart Vehicales Surveillance in Foggy Conditions Using Enhanced Deep Learning Algorithms. 45(3), 914–929.

Shaik, M. E., Islam, M. M., & Hossain, Q. S. (2021). A review on neural network techniques for the prediction of road traffic accident severity. Asian Transport Studies, 7, 100040. https://doi.org/10.1016/j.eastsj.2021.100040

Shi, C., & Zhang, X. (2023). Recurrent neural network wind power prediction based on variational modal decomposition improvement. AIP Advances, 13(2). https://doi.org/10.1063/5.0135711

Sivalingan, H (2024). Cloud-Smart Surveillance: Enhancing Anomaly Detection In Video Streams With Df-Convlstm-Based Vae-Gan. Kufa Journal of Engineering, 15(4), 125–140. https://doi.org/10.30572/2018/KJE/150409

Verma, R., & Agarwal, M. M. (2024). Enhancing Road Accident Prediction : An Advanced Information Retrieval Approach with Enhanced Focal Loss. Library of Progress-Library Science, Information Technology & Computer , 44(3), 13679–13690.

Verma, R., & Agarwal, M. M. (June 2025). A systematic review on road accident prediction: A special attention towards machine learning and deep learning approaches. Journal of Circuits, Systems and Computers. https://doi.org/10.1142/S0218126625300090

Verma, R., & Agarwal, M. M. (March 2025). Enhancing Road Accident Classification with Capsule Recurrent Neural Network and Improved Reptile Search Algorithm. IETE Journal of Research, 71(5), 1822–1841. https://doi.org/10.1080/03772063.2025.2464239.

Verma, R., and Agarwal, M. M. (April 2025). Road Accident Severity Prediction using Adaptive Custom Weight Initialization and Enhanced Focal Loss Integration Technique. IETE Journal of Research, 1-13. https://doi.org/10.1080/03772063.2025.2487628

Yang, C., Wang, W., Zhang, X., Guo, Q., Zhu, T., & Ai, Q. (2021). A Parallel Electrical Optimized Load Forecasting Method Based on Quasi-Recurrent Neural Network. IOP Conference Series: Earth and Environmental Science, 696(1), 012040. https://doi.org/10.1088/1755-1315/696/1/012040

Yang, J., Li, J., Wei, L., Gao, L., & Mao, F. (2022). ST-AGRNN: A Spatio-Temporal Attention-Gated Recurrent Neural Network for Traffic State Forecasting. Journal of Advanced Transportation, 2022, 1–17. https://doi.org/10.1155/2022/2806183

Zhang, T., Ding, W., & Xing, M. (2023). Attention-based Dynamic Graph Convolutional Recurrent Neural Network for Traffic Flow Prediction in Highway Transportation. http://arxiv.org/abs/2309.07196