Road Accident Detection using SVM and Learning: A Comparative Study

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***Abstract*—Everyday, a great deal of children and young adults (aged five to 29) lives are lost in road accidents. The most frequent causes are a driver's behavior, the streets infrastructure is of lower quality and the delayed response of emergency services especially in rural areas. There is a need for automatics road accident systems detection that can assist in recognizing road accidents and determining their positions. This work reviews existing machine learning approaches for road accidents detection. We propose three distinct classifiers: Convolutional Neural Network CNN, Recurrent Convolution Neural Network R-CNN and Support Vector Machine SVM, using a CCTV footage dataset. These models are evaluated based on ROC curve, F1 measure, precision, accuracy and recall, and the achieved accuracies were 92%, 82%, and 93%, respectively. In addition, we suggest using an ensemble learning strategy to maximize the strengths of individual classifiers, raising detection accuracy to 94%.**

Keywords—Road accidents; road traffic management; machine learning; SVM; deep learning; ensemble learning

I. Introduction

According to provisional statistics from World Health Organization (WHO), road accidents cause around 1.3 million deaths in a year. There are several common reasons for these death include pre-accident and post-accident causes; the first state includes bad weather condition, inadequate road infrastructures, and driver behavior, the second state, most of the time it refer to delayed response from emergency department, which can prevent victims from receiving immediate first aid in severe accident cases [1].

When a traffic incident occurs, an alert system conducts periodic surveys and generates notifications that offer clear information about type and location of accidents [2], [3] and [4], to take the appropriate actions and minimize number of incidents death. Many digital and traditional solutions were explored to avoid and detect accidents; the digital solution has been investigated in smart city projects that handle various areas of urban development including road management and control. These projects integrate a wide range of technologies such as computer vision, Internet of things (IoT) technologies [5], Blockchain [6], Vehicle Ad hoc Network (VANET) approaches and communication technologies like 5G wireless networks.

Since the 1980s, many researches have been investigating various approaches for quickly and correctly identifying crashes to aid in traffic accident management (GSM, GPS, Radar). The study of [7] provides an overview of automatic road accident detection systems used to save victims, these systems use GPS, GSM, and mobile applications. In study [8], the authors proposed two Blockchain-based accident detection approaches. The goal is to improve the detection of legal infractions and the accompanying measures. So, an offline-detection method described, which is aimed at detecting of accidents in absence of internet. And study in [9] suggest a system designed for autonomous vehicles, capable of identifying vehicle accidents using a dashboard camera. The research in [10] outlined the techniques employed in computer vision to detect and track moving objects.

The intelligent transport system (ITS) is basically a system that employs new Information and Communication Technologies (ICT) to communicate the vehicles to each other (vehicle to vehicle V2V) or ensure communication between vehicles and road infrastructure (vehicle-to-infrastructure V2I) through a transport network. ITSs technology helps to streamline the transportation sector, assisting in resolving issues with accidents, pollution, traffic congestion on roads, and prevention of collisions, as well as assisting in the safety transport networks and real time traffic condition monitoring [11] and [1].

Despite the numerous advantages of IoT and AI over traditional information and communication technology (ICT), establishing a relevant alert system remains a challenge. Hence, it is imperative to discover an efficient approach. Our study doesn't aim to propose a solution for an automatic system in cars for collision detection (ITS), we are concentrating on developing an ideal road accident detection model that will be utilized in conjunction with an alert system. We propose a model for accident detection on rural or remote roads to inform the emergency services immediately.

The following are the study's main contributions:

- A comprehensive system model to detect road accident.
- Investigation of machine learning-based approaches for event detection.
- Testing and validating of the proposed models by contrasting with the state-of-the-art techniques.

The format of the paper is as follows: Section II highlights past studies on the detection and prediction of traffic accidents using deep learning and machine learning. The approach and the general model's structure are presented in Section III. The proposed model results and the positive effects of adopting ensemble learning in our situation are covered in Section IV.

Section V provides a conclusion and recommendations for future research directions.

II. Related Work

Machine learning has sparked significant interest and shown great promise in different domains. In healthcare, it helps with disease diagnosis and prediction [12], [13] and [14], improving patient care [15] and [16]. In finance, machine learning methods examine large databases to identify fraudulent activity, enhance investment plans. Also recommendation systems depend heavily on machine learning, which has revolutionized the way people find relevant content and items on a variety of platforms [17], [18] and [19]. In road traffic management, machine learning has become crucial for optimizing traffic flow and enhancing safety through innovative applications like accident detection and prediction systems. In the following paragraphs, we present different applications and classification models of accident detection:

Many research has been produced on accident identification and information systems using deep learning [20]. The authors of [21] proposed a deep learning strategy for autonomous identification and localization of traffic accidents. This strategy involves applying a spatio-temporal auto-encoder to model spatial representation and a sequence-to-sequence long short-term memory auto-encoder to model temporal representation in the video.

The study of Trung [22] create the Attention R-CNN accident detection network, with comprises two sources one for detecting thing with classes and one for determining their state (safe, dangerous, or crashed).

The research in [1] describes a method for intelligent traffic accident detection in which automobiles share tiny vehicle data with one another. The suggested system collects simulated data from vehicular ad hoc networks (VANETs) based on vehicles speeds and coordinates to broadcasts traffic alarms to drivers. DETR (Detection Transformers) and Random Forest classifier are used to detect traffic accidents [3]. Objects in CCTV footage such as automobiles, bicycles, and people are spotted using the DETR, and the features are sent to a Random Forest Classifier for frame-by-frame classification. Each video frame is classed as either an accident frame or a non-accident frame.

The proposed method in [23] looks to predict wrong-lane incidents with the Decision Tree (DT) algorithm, it was applied to a road accident dataset comprises 1834 records.

The suggested system of [24] will collect essential details from automobiles that are near to each other and analyze the data using machine learning algorithms to find possible accidents.

The k-mean++ is used in [25] to identify the causes leading to these accidents in every area of India, and to determine the severity of each factor.

In study [26], it process every single frame of video through a deep learning convolution neural network model and determine whether the state is an accident or non-accident.

The practicality of utilizing deep learning methods to recognize accident events and estimate the danger of crashes is investigated in study [27]. Data obtained through roadside radar sensors on volume, speed, and sensor.

The study proposed by [28] present deep learning model to identify and forecast road incident by amalgamating data derived from twitter with additional data such as emotions, weather, geo-coded location..., The findings demonstrate that the accuracy of accident detection has increased by 8%, bringing the test accuracy to 94%.

III. Proposed Work

The main idea is to investigate on machine learning approaches to choose the most prevent model for road accident detection. Fig. 1 shows the global architecture, we train three models such as SVM, CNN and RCN, we use a specific data preprocessing for each classifier. We discuss separately each model later.

A. Dataset

We download the dataset from Kaggle [29], it contains CCTV footage frames of accidents and non-accidents, split into train, test and validation folders, the details of the dataset are given in Table I.

The used dataset divided into four categories: vehicles collision, cars motorcyclist collision, pedal cyclist collision, vehicle pedestrian collision.

TABLE I. Count of Frames of used Dataset

	Train	**Test**	**Validation**
Accident frames	369	47	46
Normal frames	422	54	52

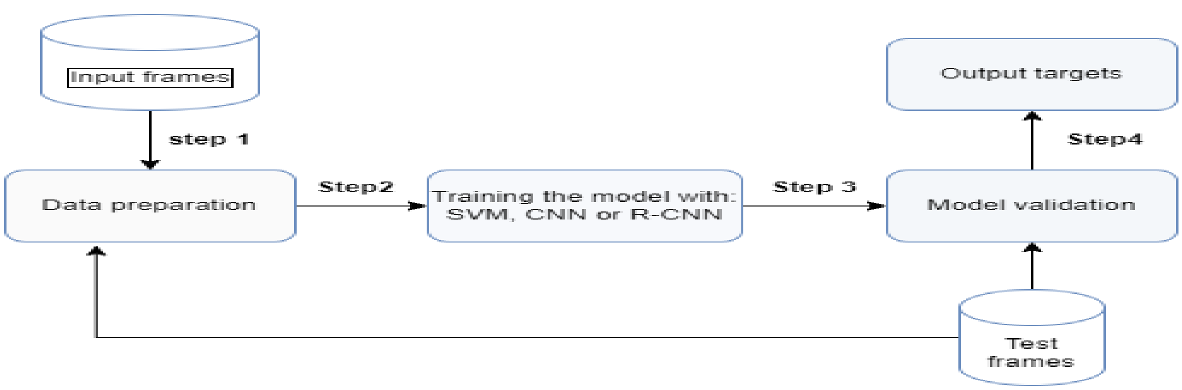

Fig. 1. Global architecture of proposed methodology.

B. Machine Learning Algorithms

After preparing the data, we use five classifiers, which are: CNN, R-CNN, Random Forest, SVM and LSTM. In this comparative study we choose to compare between deep learning classifier (CNN and RCNN) and SVM because they achieve best accuracies.

1) CNN: CNN is one of the used algorithms used in this study, our model is structured as presented in Fig. 2. Its structure is formed from two convolutional layers with pool layers for feature extraction and two fully connected layers for classification:

a) Convolutional layer: Its goal is to extract the distinctive features for every image by compressing it to decrease its initial size.

In our case, we trained a model with two convolutional layers using ReLu activation method, the first one has three input channels (RGB images) and 32 output channels, with a 3x3 kernel and one pixel padding.

The second convolutional layer has 32 channels (from output of first convolutional layer) and 64 output channels, using a 3x3 kernel and 1 pixel for padding.

b) Pooling layer: The feature maps size is reduced by pooling layers. As a result, it reduces the number of parameters to learn as well as the computation done in the network. There are three types of pooling; max pooling, average pooling and sum pooling. In the proposed model we used max pooling with 2x2 kernel and stride of 2.

c) Flatten: This step refers to reshape the feature maps into a one dimensional vector while saving all individual elements.

d) Fully connected layer: In this layer, every single neuron is connected to all neurons in previous layer, resulting in a completely connected network structure.

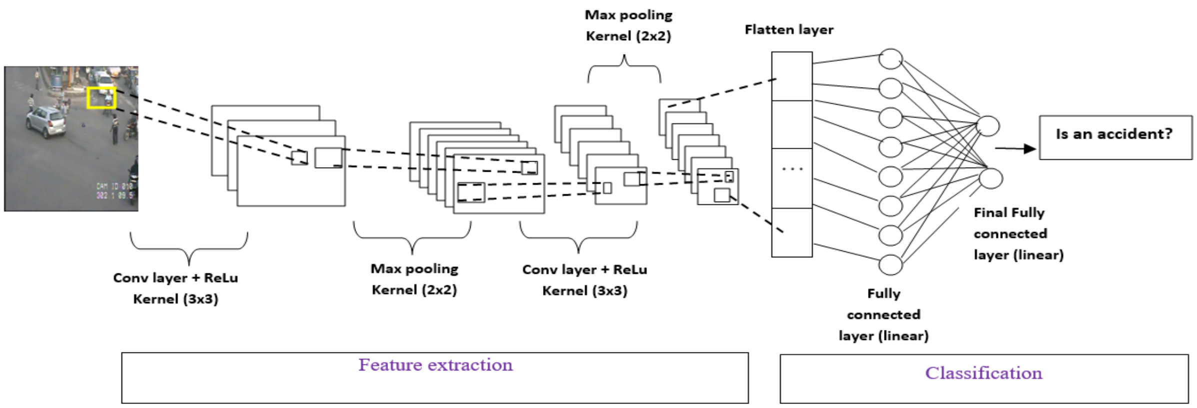

Fig. 2. The proposed CNN model for road accidents detection.

2) R-CNN: RCN is another used classifier in this study, this model is structured as shown in Fig. 3. Its architecture is formed from one convolutional layers with pool layer for feature extraction followed by LSTM layer and one fully connected layer for classification.

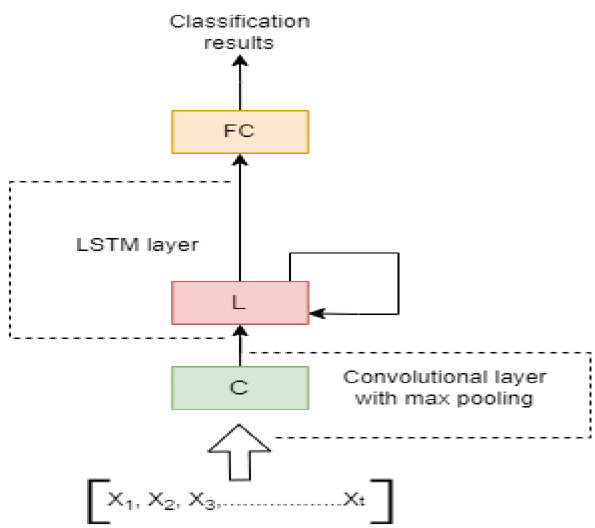

Fig. 3. Recurrent convolutional neural network structure.

3) SVM: SVM is the third proposed classifier in this research, Fig. 4 show its schema:

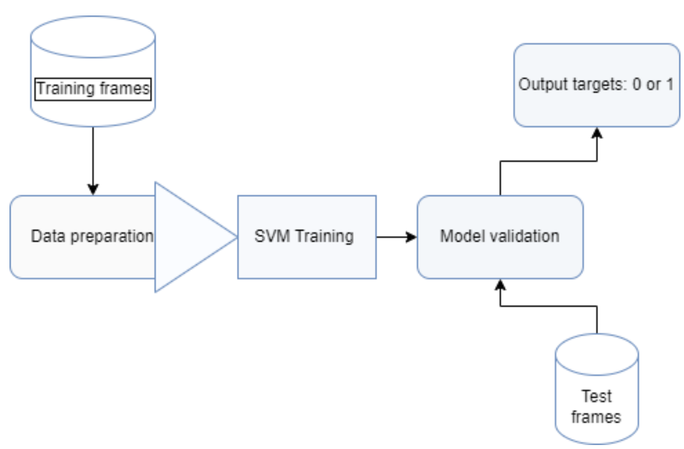

Fig. 4. Model construction based SVM.

a) Data preprocessing: In this step, the frames are resized, converted from BGR to RGB format and the pixels are normalized to be between 0 and 1 by transforming the image to float32 and dividing by 255.0.

b) Used algorithms: SVM algorithm aims to separate the given dataset as best as possible by utilizing a kernel, which can transform the low dimensional input space to a high dimensional space.

There are such parameters, in our case we use linear kernel.

C. Model Evaluation

Model evaluation is an important part of the data analytics process, which lets us know how well the model classify data, and determine the model advantages and disadvantages by evaluating its performance against real data. The receiver operator characteristic (ROC) curve is often used in the analysis of binary results to show how effective a model or algorithm is. This curve can be reduced to a single statistic, the area under the curve (AUC), and offers insights into performance across a range of criteria [30]. These measures are derived from the confusion matrix [31], which includes metrics such as false negative (FN), true negatives (TN), false positives (FP), and true positives (TP).

A confusion matrix is linked to other metrics, such as sensitivity (TPR) (5), specificity (FPR) (6), precision (2), recall (1), accuracy (4), F1 measure (3), and the area under the ROC curve (AUC), which depicts the correlation between sensitivity and 1-specificity.

$$Recall = \frac{TP}{TP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$F1 - measure = \frac{2*precision*recall}{precision+recall} \tag{3}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$TPR = \frac{TP}{TP+FN} \tag{5}$$

$$FPR = \frac{FP}{FP+TN} \tag{6}$$

IV. Result and Discussion

In this section, the results of proposed classifiers are presented. The used test set contains 100 instances which divided into accident and non-accident of CCTV frames. The test findings demonstrated that the false positives were relatively few, indicating the stability of models. False positive values are 16, 2, and 2 of R-CNN, SVM and CNN respectively as shown in confusion matrix in Fig. 8.

1) Evaluation of R-CNN classifier: Our proposed recurrent CNN classifier combines convolutional layer and LSTM layer. The results of fitting process are depicted in Fig. 5, which show relatively few negative and false positive predictions. This proves how well the model can distinguish between frames of traffic accidents and non-accidents.

2) Evaluation of simple SVM classifier: Below are the evaluation results of classifier based SVM (see Fig. 6), which demonstrate that the model is good in distinguish between frames with and without traffic accident.

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Classification report of RCN classifier:
              precision    recall  f1-score   support

           0       0.73      0.94      0.82        47
           1       0.93      0.70      0.80        53

    accuracy                           0.81       100
   macro avg       0.83      0.82      0.81       100
weighted avg       0.83      0.81      0.81       100
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Fig. 5. Classification report of recurrent CNN model.

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Classification report of SVM classifier:
              precision    recall  f1-score   support

           0       0.95      0.89      0.92        47
           1       0.91      0.96      0.94        53

    accuracy                           0.93       100
   macro avg       0.93      0.93      0.93       100
weighted avg       0.93      0.93      0.93       100
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Fig. 6. Classification report of SVM model.

TABLE II. Recall, F1 Score and Precision of SVM and Deep Learning Classifiers

		Recall	F1 score	Precision
Accident	R-CNN	0,7	0,8	0,93
	CNN	0,96	0,93	0,89
	SVM	0,96	0,94	0,91
	Ensemble learning	0,98	0,95	0,91
Non-accident	R-CNN	0,94	0,82	0,73
	CNN	0,87	0,91	0,95
	SVM	0,89	0,92	0,95
	Ensemble learning	0,89	0,93	0,98

3) Evaluation of simple CNN classifier: CNN classifier is accurately differentiating between positive and negative frames compared to R-CNN. Training accuracy and validation accuracy values are closely aligned, indicating the absence of overfitting in Fig. 7.

An illustrated summary of the different metrics used for the research purpose is provided, such as recall, F1 score, accuracy, precision and receiver operating characteristic ROC curve, as presented in Table II, and in Fig. 9 and Fig. 10.

SVM and Ensemble learning, in this work, have shown better performance than deep learning techniques. This is explained by the nature of dataset and its smaller size. In addition, manual extraction and feature engineering have the potential, in this case, to extract relevant features. In term of accuracy, SVM achieved 93%, CNN has 92% and R-CNN has 82%.

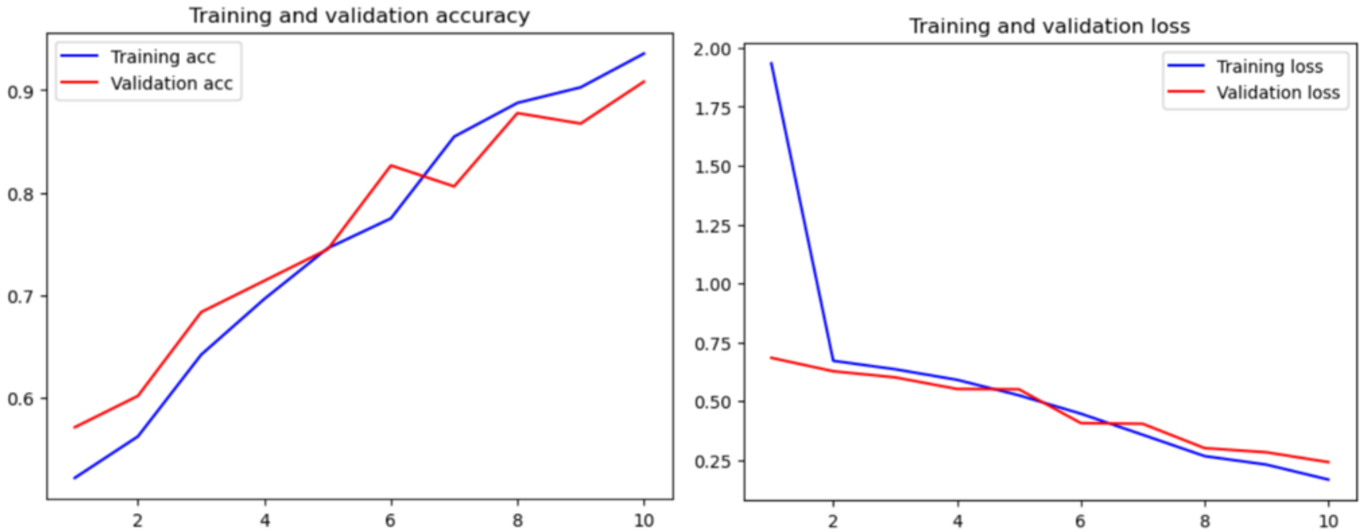


Fig. 7. Left, line plot of CNN loss on train and validation datasets. Right figure, line plot of CNN accuracy on train and validation datasets.

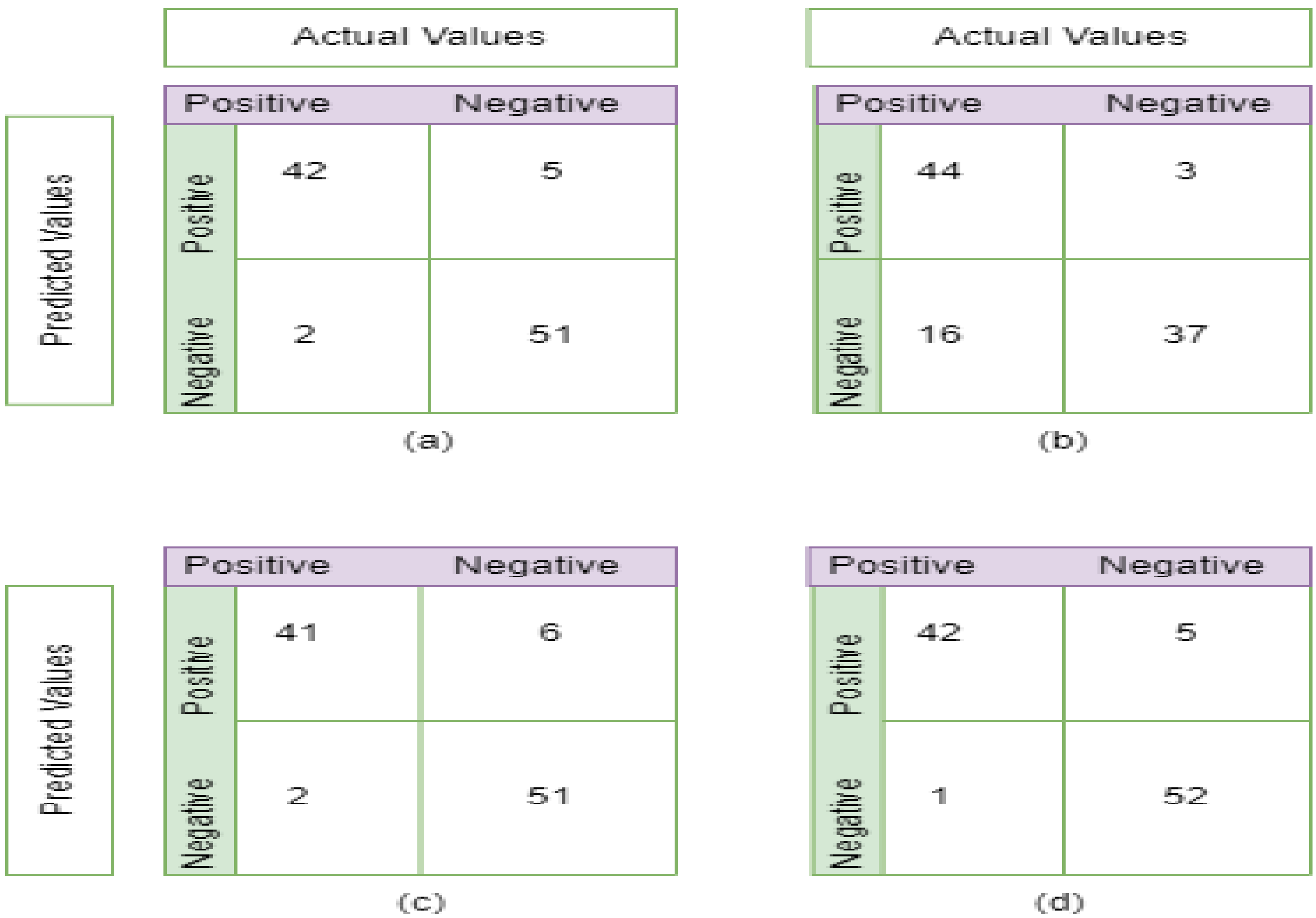


Fig. 8. Confusion matrix of: (a) SVM, (b) R-CNN, (c) CNN and (d) Ensemble learning.

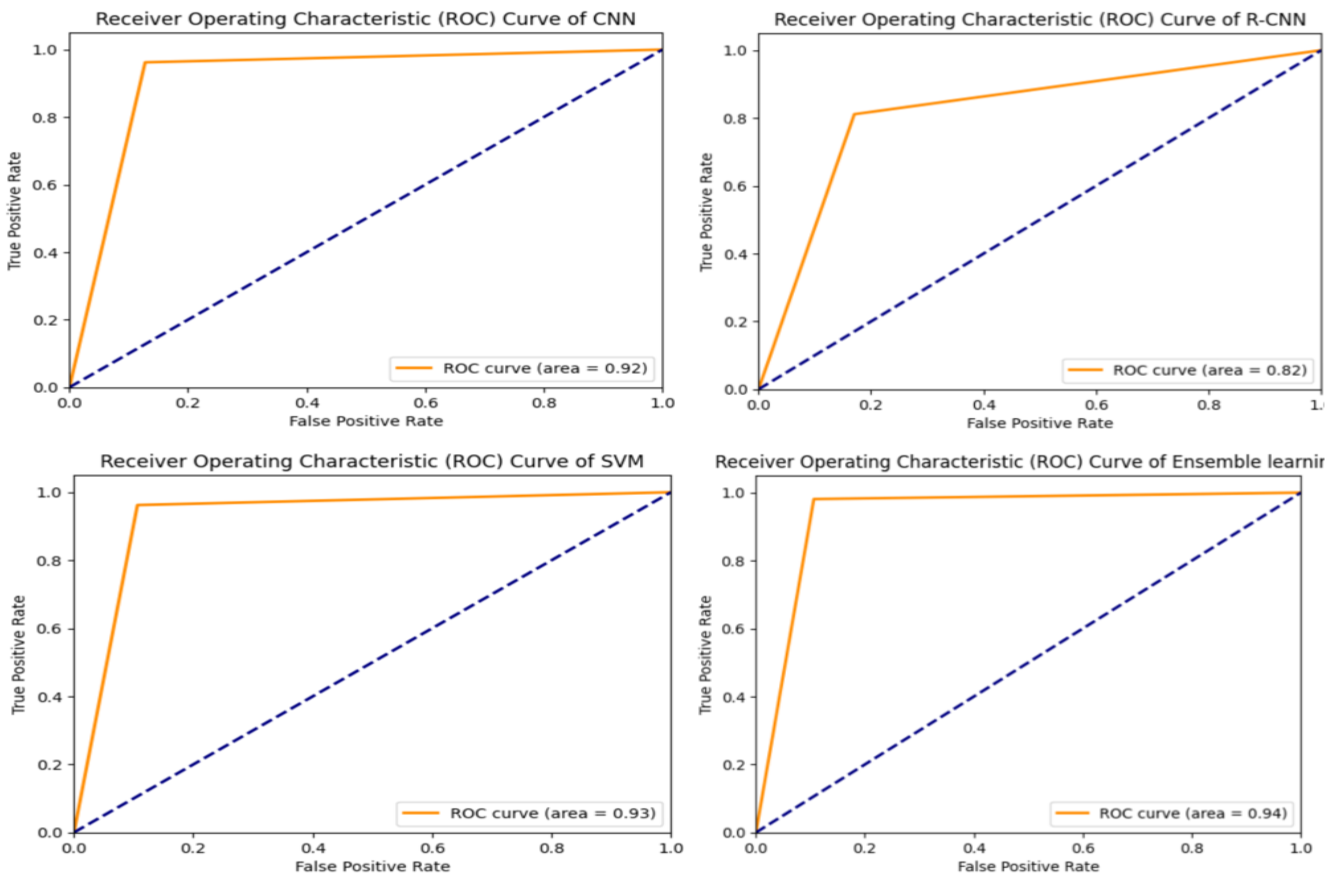
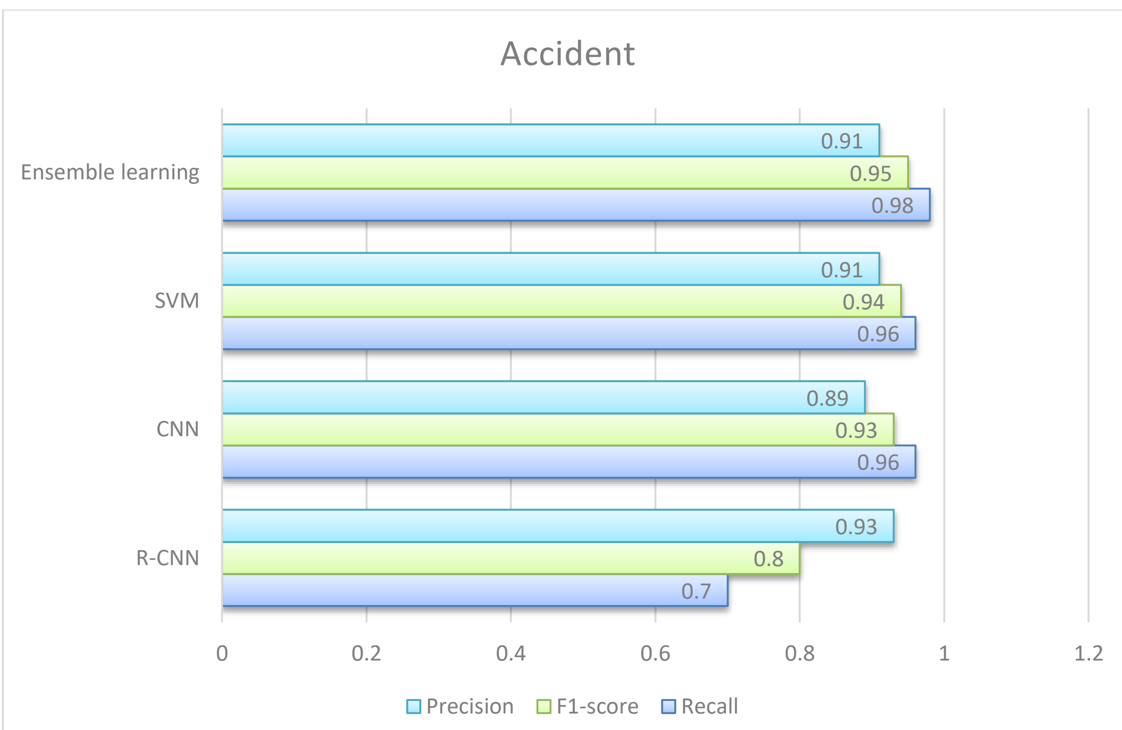


Fig. 9. Receiver Operating Characteristic (ROC) curves of the proposed classifiers.



(a)

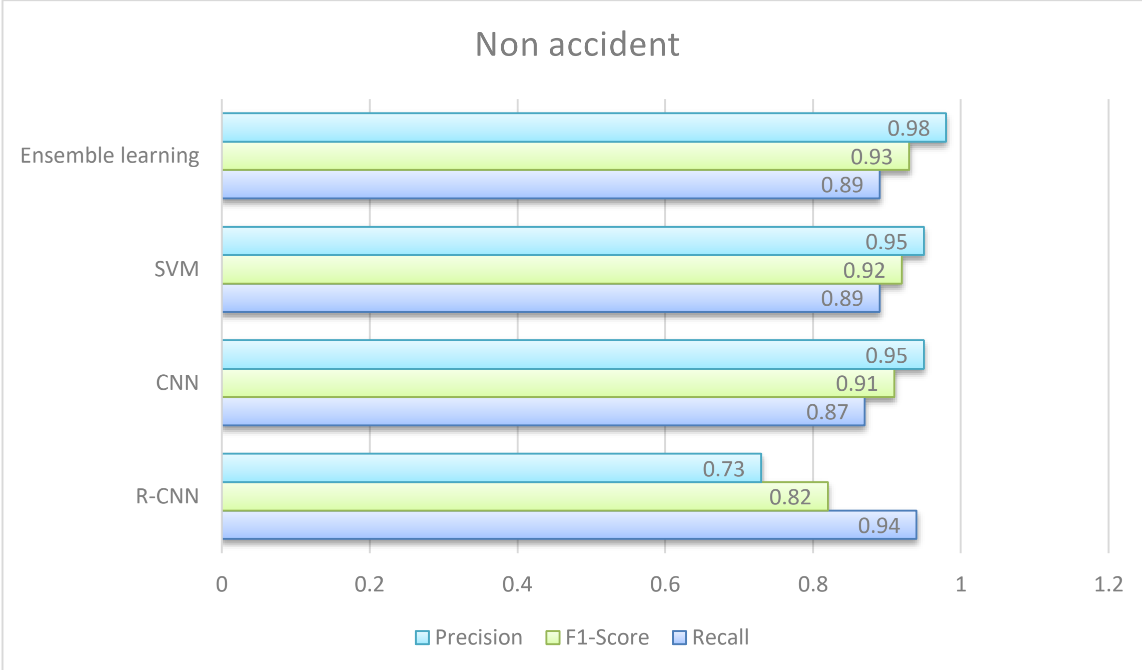


Fig. 10. (a): Comparison of classifiers in recall, F1 score and precision of accident detection. (b): Comparison of classifiers in recall, F1 score and precision of non-accident detection.

TABLE III. COMPARISON SUGGESTED MODELS WITH PREVIOUS WORKS BASED ON F1 SCORE AND ACCURACY

Reference	Dataset	Classification technique	F1 measure	Accuracy
K. Pawar et V. Attar [21]	4677 videos of accident and non-accident cases	LSTM auto-encoder	78,58%	-
S. Ghosh, S. J. Sunny, et R. Roney [26]	CCTV camera frames	CNN with LSTM	-	92,38%
T. Huang, S. Wang, et A. Sharma [27]	Accident frames : 447043 Non-accident frames : 447043	Random forest	74%	76%
Our model-1	791 frames of accident and non-accident cases	R-CNN	81%	82%
Our model-2	791 frames of accident and non-accident cases	CNN	92%	92%
Our model-3	791 frames of accident and non-accident cases	SVM	93%	93%
Our model-4	Same dataset	Ensemble learning using CNN, R-CNN and SVM	94%	94%

According to the comparison in Table III, the SVM classifier performed better in this situation compared to deep learning models. This result is consistent with earlier studies by [21] and [26], which showed that, on smaller datasets, conventional machine learning models like SVM can outperform deep learning algorithms.

The experimental outcomes, reveal that the ensemble learning approach achieved the highest accuracy of 94%, followed by the SVM at 93%, CNN at 92% and recurrent CNN at 82%. Combining the predictions of traditional and deep learning models through the averaging method yielded higher performance metrics compared to using them separately. This approach resulted in improved predictions of road accidents, as demonstrated in the example depicted in Fig. 11 and Fig. 12.

Predicted Class: non-accident

Fig. 11. Prediction of absence of road accident by ensemble learning approach.

Predicted Class: accident

Fig. 12. Prediction of road accident applying ensemble learning approach.

V. Conclusion and Future Perspective

In this study, we developed three road accident classifiers, which are SVM, CNN, and RCN. We evaluated and compared these models in terms of precision, accuracy, recall, F1 score and ROC curve. The accuracy of these models was 93%, 92%, and 82% respectively. These findings indicate that the SVM strategy outperforms deep learning algorithms using a small dataset of CCTV footage frames. Detection of road accident plays an important role at improving accident emergency response. Is crucial to have a model with high and well prediction. To enhance accuracy, we combine the predictions of these models through ensemble learning technique, we get 94%. As a part of future perspectives, an NLP and computer vision approaches can be used to predict the probability of accident occurrence by analyzing driver's behavior.

References

[1] N. Dogru et A. Subasi, « Traffic accident detection using random forest classifier », in 2018 15th Learning and Technology Conference (L&T), Jeddah: IEEE, févr. 2018, p. 40-45. doi: 10.1109/LT.2018.8368509.

[2] M. M. Hamdi, L. Audah, S. A. Rashid, et S. Alani, « VANET-Based Traffic Monitoring and Incident Detection System: A Review », IJECE, vol. 11, no 4, p. 3193, août 2021, doi: 10.11591/ijece.v11i4.pp3193-3200.

[3] A. Srinivasan, A. Srikanth, H. Indrajit, et V. Narasimhan, « A Novel Approach for Road Accident Detection using DETR Algorithm », in 2020 International Conference on Intelligent Data Science Technologies and Applications (IDSTA), Valencia, Spain: IEEE, oct. 2020, p. 75-80. doi: 10.1109/IDSTA50958.2020.9263703.

[4] I. Benallou, A. Azmani, et M. Azmani, « Evaluation of the Accidents Risk Caused by Truck Drivers using a Fuzzy Bayesian Approach », IJACSA, vol. 14, no 6, 2023, doi: 10.14569/IJACSA.2023.0140620.

[5] S. U. Hassan, J. Chen, T. Mahmood, et A. Akbar, « Accident Detection and Disaster Response Framework Utilizing IoT », IJACSA, vol. 11, no 3, 2020, doi: 10.14569/IJACSA.2020.0110348.

[6] H. E. Mazouzi, A. Khannous, K. Amechnoue, et A. Rghioui, « Security Challenges Facing Blockchain Based-IoV Network: A Systematic Review », IJACSA, vol. 14, no 5, 2023, doi: 10.14569/IJACSA.2023.0140526.

[7] U. Khalil, T. Javid, et A. Nasir, « Automatic road accident detection techniques: A brief survey », in 2017 International Symposium on Wireless Systems and Networks (ISWSN), Lahore: IEEE, nov. 2017, p. 1-6. doi: 10.1109/ISWSN.2017.8250025.

[8] V. Davydov et S. Bezzateev, « Accident Detection in Internet of Vehicles using Blockchain Technology », in 2020 International Conference on Information Networking (ICOIN), janv. 2020, p. 766-771. doi: 10.1109/ICOIN48656.2020.9016602.

[9] D. Chand, S. Gupta, et I. Kavati, « Computer Vision based Accident Detection for Autonomous Vehicles », in 2020 IEEE 17th India Council International Conference (INDICON), New Delhi, India: IEEE, déc. 2020, p. 1-6. doi: 10.1109/INDICON49873.2020.9342226.

[10] V. Zinchenko, G. Kondratenko, I. Sidenko, et Y. Kondratenko, « Computer Vision in Control and Optimization of Road Traffic », in 2020 IEEE Third International Conference on Data Stream Mining & Processing (DSMP), Lviv, Ukraine: IEEE, août 2020, p. 249-254. doi: 10.1109/DSMP47368.2020.9204329.

[11] Sant Longowal Institute of Engineering & Technology, India, T. Garg, G. Kaur, et Sant Longowal Institute of Engineering & Technology, India, « A Systematic Review on Intelligent Transport Systems », JCCE, juin 2022, doi: 10.47852/bonviewJCCE2202245.

[12] H. El Massari, N. Gherabi, S. Mhammedi, H. Ghandi, F. Qanouni, et M. Bahaj, « An Ontological Model based on Machine Learning for Predicting Breast Cancer », IJACSA, vol. 13, no 7, 2022, doi: 10.14569/IJACSA.2022.0130715.

[13] F. Qanouni, H. Ghandi, N. Gherabi, et H. El Massari, « Machine Learning Models for Detection COVID-19 », in Advances in Intelligent System and Smart Technologies, N. Gherabi, A. I. Awad, A. Nayyar, et M. Bahaj, Éd., Cham: Springer International Publishing, 2024, p. 95-108. doi: 10.1007/978-3-031-47672-3_12.

[14] H. El Massari, N. Gherabi, S. Mhammedi, H. Ghandi, M. Bahaj, et M. Raza Naqvi, « The Impact of Ontology on the Prediction of Cardiovascular Disease Compared to Machine Learning Algorithms », Int. J. Onl. Eng., vol. 18, no 11, p. 143-157, août 2022, doi: 10.3991/ijoe.v18i11.32647.

[15] H. El Massari, N. Gherabi, S. Mhammedi, H. Ghandi, F. Qanouni, et M. Bahaj, « Integration of ontology with machine learning to predict the presence of covid-19 based on symptoms », Bulletin EEI, vol. 11, no 5, p. 2805-2816, oct. 2022, doi: 10.11591/eei.v11i5.4392.

[16] H. El Massari, N. Gherabi, S. Mhammedi, Z. Sabouri, H. Ghandi, et F. Qanouni, « Effectiveness of applying Machine Learning techniques and Ontologies in Breast Cancer detection », Procedia Computer Science, vol. 218, p. 2392-2400, 2023, doi: 10.1016/j.procs.2023.01.214.

[17] S. Mhammedi, H. El Massari, et N. Gherabi, « Composition of Large Modular Ontologies Based on Structure », in Advances in Information, Communication and Cybersecurity, Y. Maleh, M. Alazab, N. Gherabi, L. Tawalbeh, et A. A. Abd El-Latif, Éd., Cham: Springer International Publishing, 2022, p. 144-154. doi: 10.1007/978-3-030-91738-8_14.

[18] F. Nafis, K. A. Fararni, A. Yahyaouy, et B. Aghoutane, « An Approach based on Machine Learning Algorithms for the Recommendation of Scientific Cultural Heritage Objects », IJACSA, vol. 12, no 5, 2021, doi: 10.14569/IJACSA.2021.0120529.

[19] G. Rysbayeva et J. Zhang, « Sequence Recommendation based on Deep Learning », International Journal of Advanced Computer Science and Applications, vol. 14, no 2, 2023.

[20] V. Sherimon et al., « An Overview of Different Deep Learning Techniques Used in Road Accident Detection », IJACSA, vol. 14, no 11, 2023, doi: 10.14569/IJACSA.2023.0141144.

[21] K. Pawar et V. Attar, « Deep learning based detection and localization of road accidents from traffic surveillance videos », ICT Express, vol. 8, no 3, p. 379-387, sept. 2022, doi: 10.1016/j.icte.2021.11.004.

[22] T.-N. Le, S. Ono, A. Sugimoto, et H. Kawasaki, « Attention R-CNN for Accident Detection », in 2020 IEEE Intelligent Vehicles Symposium (IV), Las Vegas, NV, USA: IEEE, oct. 2020, p. 313-320. doi: 10.1109/IV47402.2020.9304730.

[23] «Wrong-Lane Accidents Detection using Random Forest Algorithm in comparison with Decision Tree for Improved Accuracy », pnr, vol. 13, no SO4, janv. 2022, doi: 10.47750/pnr.2022.13.S04.060.

[24] B. K. M, A. Basit, K. MB, G. R, et K. SM, « Road Accident Detection Using Machine Learning », in 2021 International Conference on System, Computation, Automation and Networking (ICSCAN), juill. 2021, p. 1-5. doi: 10.1109/ICSCAN53069.2021.9526546.

[25] U. K.M., « Road Accident Perusal Using Machine Learning Algorithms », IJPR, vol. 24, no 5, p. 1676-1682, mars 2020, doi: 10.37200/IJPR/V24I5/PR201839.

[26] S. Ghosh, S. J. Sunny, et R. Roney, « Accident Detection Using Convolutional Neural Networks », in 2019 International Conference on Data Science and Communication (IconDSC), Bangalore, India: IEEE, mars 2019, p. 1-6. doi: 10.1109/IconDSC.2019.8816881.

[27] T. Huang, S. Wang, et A. Sharma, « Highway crash detection and risk estimation using deep learning », Accid Anal Prev, vol. 135, p. 105392, févr. 2020, doi: 10.1016/j.aap.2019.105392.

[28] A. Azhar et al., « Detection and prediction of traffic accidents using deep learning techniques », Cluster Comput, vol. 26, no 1, p. 477-493, févr. 2023, doi: 10.1007/s10586-021-03502-1.

[29] «Road accident dataset ». [En ligne]. Disponible sur: https://www.kaggle.com/datasets/ckay16/accident-detection-from-cctv-footage

[30] J. Muschelli, « ROC and AUC with a Binary Predictor: a Potentially Misleading Metric », J Classif, vol. 37, no 3, p. 696-708, oct. 2020, doi: 10.1007/s00357-019-09345-1.

[31] I. Düntsch et G. Gediga, « Indices for rough set approximation and the application to confusion matrices », International Journal of Approximate Reasoning, vol. 118, p. 155-172, mars 2020, doi: 10.1016/j.ijar.2019.12.008.