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* **Corresponding author**.

gkarthikeyan2007@gmail.com

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Instinctive Detection of Accident Occurrence using Numerous Machine Learning Techniques with Comparative Study

M Rajamanogaran[1], G Karthikeyan[2]*

1 PG and Research Department of Computer Science, Periyar Government Arts College, Cuddalore, 607001, Tamil Nadu, India
2 Assistant Professor, PG and Research Department of Computer Science, Periyar Government Arts College, Cuddalore, 607001, Tamil Nadu, India

Abstract

Objectives: The research work aims to develop an automated detection system that uses video captures to identify roadside accidents or significant events. By alerting nearby hospitals and emergency services, the system reduces response times and potentially saves lives. The system's integration with existing emergency response systems ensures prompt assistance to those in need. **Methods:** The video processing pipeline begins by converting video files into frames for analysis and feature extraction. These features serve as inputs for classification algorithms such as Random Forest, SVM, and KNN. The model's performance is evaluated using a training set and unseen test data, with the predicted classifications compared against the ground truth labels. **Findings:** Among the tested classification algorithms, the Random Forest algorithm achieved the highest accuracy. Using 128 frames for analysis provided more comprehensive information, yielding a 96% accuracy rate. This combination proves to be a powerful tool in classification tasks, providing reliable and accurate outputs. **Novelty:** Machine learning algorithms are instrumental in automating accident detection from video captures. They analyse video footage to identify accidents and promptly alert relevant authorities. This technology can also dispatch emergency messages to nearby hospitals, ensuring quick assistance. The consideration of different frame counts in classification improves accuracy by capturing critical moments and patterns. Machine learning algorithms applied in this work significantly enhance emergency response, reduce response times, and potentially save lives.

Keywords: Emergency Services; Accidents; Feature Extraction; Random Forest; SVM; KNN

1 Introduction

Accidents happen in sudden stage, out of control in the blink of eye with minor or major injuries and in some cases loss of lives. According to World Health Organization (WHO) and statistical report, India shares around eleven percent accidents and especially Tamil Nadu is the leading state in deadly mishaps. The main reason is the lack of immediate response and timely treatment due to the unawareness of the unexpected accident. The current situation is alarming the need for an expert system to identify the accident and rapid reaction to the concerned places. Still research work is done in this field for better action but there are more loopholes to be corrected.

The issue of roadside accident detection has been approached through various techniques in the past, ranging from sensor networks to manual reporting systems. Traditional methods often rely on eyewitness reports and the physical presence of law enforcement or emergency services personnel to identify accidents which can lead to significant delays. Existing automated systems typically use a combination of threshold-based algorithms and simple pattern recognition which may not be sensitive or specific enough to effectively discern an accident from normal traffic or benign roadside activities. A common limitation of these systems is the proportion of false positives and negatives, as well as their reliance on specific camera angles and lighting conditions.

The major challenges faced for constructing the model needed for the detection of road accidents are listed as follows. One of the key problems is the low accuracy in classification of accident in recorded videos. Accidents happening in roadside which can be misguided by various weather conditions is another delinquent situation. Another paramount problem is the poor response system needed for emergency cases due to lack of proper messaging facilities. A skillful model is desired to address the existing complications using multi frame approach in captured videos and advanced algorithms. The model works in diverse environment showing the best result in identifying the accidents. Hybrid combination of feature extraction method with Random Forest classifier reduces misinterpretation increasing automatic alerts and dispatch services in responding the post- accident disputes.

To address these limitations, our proposed model leverages advanced machine learning algorithms and a robust frame decomposition strategy which enhances recognition performance under a variety of conditions. By employing a Random Forest classifier, which is renowned for its high accuracy and ability to handle unbalanced data and noisy environments, this method surpasses the typical threshold and pattern detection systems' sensitivity and specificity. The statistical reports claim that India is the leading country to have majority accidents sharing around eleven per cent globally and Tamil Nadu stands first in India for road accidents and further consequences. The researcher proposed that the rise in the count of accidents is due to surplus usage of vehicles especially two wheelers and four wheelers accompanied by over speed and lack of facilities to avoid the occurrence [1].

Table 1 depicts the count of major accidents happening throughout India by the survey taken in the leading states.

Table 1. Recent survey of Accidents in India

States	Number of Road Accidents
Tamil Nadu	55682
Madhya Pradesh	48219
Karnataka	34647
Uttar Pradesh	33711
Kerala	32759

The main target is to observe the traffic sequentially and check the vehicles behavior whether the condition is normal. Accident detection systems are gaining popularity due to the correct assessment of the accidents without direct optical interaction. Proper message passing to the control room and hospitals are also a part of the system which is more advantageous.

The root causes of accidents are mostly negligible in obeying traffic rules and proper assessment of traffic signals which need vigorous monitoring systems to avoid mishaps. Artificial Intelligence plays a major role in tracking vehicles nowadays to avoid accidents and monitoring systems for further actions [2]. AI combined with machine learning algorithms provide great success in detecting accidents compared with other methods. This researcher proposed a traffic accident detection [3] method for connected and automated transport systems using grid-based parameter extracting and SVC-based traffic state classification. The method achieves an 87.72% accident detection rate and higher precision than SVM and ANN models, improving accident handling and urban traffic management.

1.1 Background Works

Accidents are unavoidable in current situation due to heavy traffic and automobile congestion, so necessary steps should be considered for recovery of accidents. Immediate ambulance support and security measures on time are needed for alerting purpose to avoid the fatal effects of disasters. This work focused the location of the tragedy primarily using accident detection warning system using IOT and mobile applications[(4)]. Using this app, initially the vehicle will be identified, and messages will be approved through the arrangement in-built in the system. Deep learning model proposed[(5)] for handle the human brain activities with the help of AI and Internet of Things. A special kit is enforced to identify collision and related details like position of the vehicle, pressure, speed, and these details are passed to the cloud. Cloud manages to send the accident information to nearby locations.

Another related study[(6)] focuses on the speed of the vehicle using car alarm application with accelerometer when car crashes or roll over. The signal is activated during mishaps with vibration sensor and passes to the ATMEGA 8A controller[(7)]. GSM alerts the control room and ambulance service for immediate actions. The author introduced in his work, Internet based device with Arduino UNO R3 microcontroller and a sensor along with GPS and GSM modules. The service provider is informed about the accident and related information like time, day, date, locality using GSM module. This research[(8)] reviews existing techniques for Multiple Vehicle Cooperation and Collision Avoidance (MVCCA) strategies in Automated Vehicles (AVs), focusing on single-vehicle collision avoidance perspectives. It provides an AI-enabled framework and decision-making model, highlighting benefits and open research issues. In this research proposes one alerting system for the drivers if the vehicle is out of control due to which accidents occur[(9)]. The information will be sent to the proper contact number if any calamity happens. Despite providing the best roads and intersections, it is difficult to completely eliminate road accidents. However, steps can be taken to reduce their impact on road users and vehicles.

The author presented a machine learning model using the XGBoost[(10)] method to predict road accidents, achieving an accuracy of 94.31%. It can be integrated into road safety systems to predict future accidents. In India, the increasing number of vehicles and advancements in transportation technology have led to a significant rise in road accidents. Two-wheelers, in particular, account for 25% of all road crash deaths. The road features and traffic flow parameters leading to RTCs associated with driver errors along an access-controlled major highway in Saudi Arabia and the results supported previous studies in comparison with the similar study contexts that looked at speed dispersion in crash occurrence and severity[(11)].

Machine Learning (ML) models to predict road accident severity using New Zealand's Road accident data from 2016-2020[(12)]. The models used include Random Forest (RF), Decision Jungle (DJ), Adaptive Boosting (AdaBoost), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (L-GBM), and Categorical Boosting (CatBoost). RF performed the best with an accuracy of 81.45%. The SHapley Additive exPlanation (SHAP) was used to interpret the RF model and found that the road category and number of vehicles involved significantly impact injury severity. Retraining the ML models with these high-ranked features increased the performances of DJ, AdaBoost, and CatBoost models by 6%, 5%, and 8%, respectively.

Internet of Things (IoT) based system to detect and classify vehicle accidents according to severity[(13)]. The system uses a variety of sensors and machine learning models, including the Gaussian Mixture Model (GMM) and Classification and Regression Trees (CART), which showed the best performance. The system aims to provide immediate response to accidents by reporting essential information to emergency services.

The machine learning framework for automated car accident detection using multimodal in-car sensors[(14)]. The framework applies state-of-the-art feature extraction methods to detect real-world driving accidents. The study evaluates five different feature extraction approaches and finds that Convolutional Neural Network (CNN) features with a Support Vector Machine (SVM) classifier yield the best results. This study proposes a contactless attendance management system using artificial intelligence. The system uses facial recognition technology to automatically record student attendance in classrooms[(15)]. It aims to improve student engagement, prevent proxy attendance, and generate detailed reports for future references.

2 Methodology

Methodology: highlights the novelty of your approach over other methods. Mention the dataset used; number of images considered; parameters considered/ how testing/ training done; the modification of existing technique done; how comparison was made with gold standards etc.

The main objective of this work is to focus the accidents that occur unpredictably and automatically pass the message to the control room and hospital for immediate remedy. The proposed method proves to be more efficient compared with traditional methods due to its innovation. Outdated methods utilize machine learning to meager extent, but the proposed method employs Random Forest algorithm in combination with an optimized frame extraction process. The choice of 128 frames for detection of accident which maximizes efficiency with accuracy makes new idea in this research work. Validation process greatly reinforces the robustness of classification model by providing accuracy rate up to 96% which is the variant of existing models. Finally, integration of detection system with emergency services provides a new template by minimizing response time in accidents which is considered as the novel impression in the proposed work. For the proposed accident detection model, the UCF-Crime benchmark dataset set is used, and it contains 150 traffic accident videos and 50 normal videos for multiple hours. Using three machine learning models, the given data set is trained and tested with three set of frames for accuracy. Once the model is constructed, real videos are used for testing purpose to predict accidents. The entire framework is given as block diagram in Figure 1.

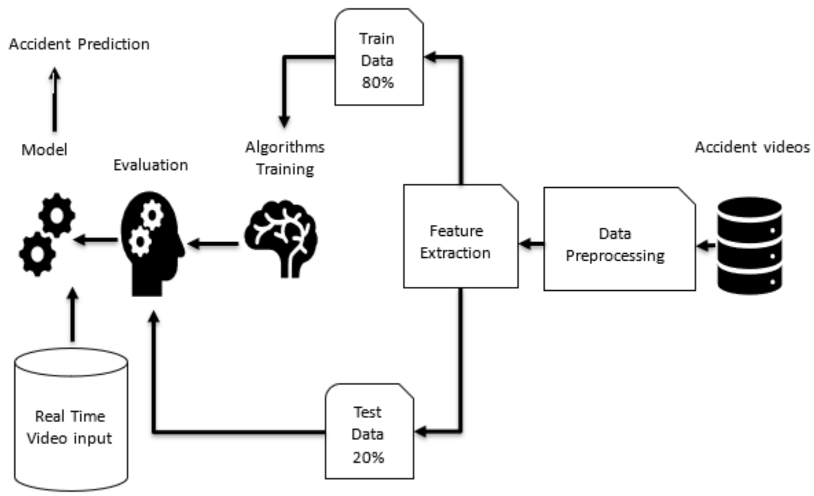

Fig 1. Basic architecture for accident event detection

The videos are collected and converted into frames of various sizes like 32, 64, 128 and trained using machine learning models for accuracy. The frames with size 128 show the highest accuracy when tested with Random Forest method.

The outline of this work is organized as follows. The following section contains pre-processing of video into frames and resizing the frames into standard size. Next section is the feature extraction method implemented on the processed image. The methods applied are statistical measures, Hu moments and GLCM methods. The succeeding section is the classification methods done to classify the accident videos with normal ones. The machine learning algorithms used are Random Forest method, SVM and KNN models. The final part is the conclusion where the results are analysed for accuracy.

2.1 Image Acquisition

Usually for the proposed method, real images are required but accidents cannot be depicted in live so recorded images or videos are used for training and testing purposes. The video data set used are extracted from UCF crime data collection which is a pack of videos in various fields like burglary, arrest, assault, explosion, road accidents, robbery etc. In this data set, each tenth frame is derived from entire video sequence and shared for each video in that particular class. All the images are in .PNG format of standard size. This data set is wide to capture 128 hours running videos with lengthy and outcropped video scenes of various incidents.

2.2 Pre-Processing of Images

The video samples extracted from the given data set are first pre-processed for further exploration. This step is crucial because the raw data is converted into suitable form by presenting only related aspects needed for machine learning model in classification. The main benefit of preparing the data is to reduce the training time and processing power when algorithm is tested on the data. In the proposed model, two standard methods are used for pre-processing to avoid quality issues and ignore irrelevant information. They are:

1. The collected videos are converted into frames of three regular sizes.
2. The frames are resized to particular dimensions of 200 x 200 pixels.

2.3 Conversion of videos into frames

The extracted videos either from online or video repository are pre-processed for extension usage. Following are the steps for conversion. They are:

1. For classification purpose, particular frames should be separated from video data based on the time and the number of frames arranged in order.
2. The video file name is necessary for processing and video is recorded using Video Capture function.
3. The vital attribute used is Frames Per Second (FPS) and get function is used to retrieve a specific frame.
4. Next the frame can be identified using the number and this number is calculated with number of frames per second and the exact time.
5. Two functions namely 'set' and 'read' are used to fix the position of the video and extract the frame from the video data.
6. Finally, the extracted frames are saved, and three sets of frames are extracted for the model.

2.4 Resizing of frames

After extracting frames from the video data, they are formatted into standard size like 200 x 200 for feature extraction. For changing the shape of the frame, the systematic method used is interpolation method based on pixel relation theory. Inter area method is used to reduce the size of the image to the required shape. This method coordinates the average value of the surrounding pixels in the frame in all dimensions and calculates the new value based on the multiples of old value. Thus, resolution is restored and there is no loss of information.

Hence, the frames are pre-processed and forwarded for extracting the needed features using the above-mentioned popular methods.

2.5 Feature Extraction Methods

Feature extraction spots the relevant and vital features from the huge data set needed for processing. The raw data is converted into mathematical and statistical attributes used for exploration while retaining the original fact in the data set. This transformation is suitable for processing with machine learning algorithms since the text or image data cannot be understood by the models used for classification. Three standard and statistical metrics used for measuring the extracted features are mean, variance and standard deviation. Other two popular measures are Hu Moments and GLCM methods.

2.6 Statistical Features

Statistical characteristics such as mean, variance, and Standard Deviation (SD), known as expressive measurements, are derived as features from the provided dataset. These features are used to produce initial symptoms to achieve classification results as whether accident occurred in the particular scene of the video. Generally, first order measurement provides data related to the grey- level circulation of the image.

2.6.1 Mean

Mean is the statistical measure used to check the similarities of two data sets with mathematical expressions and find out the difference between the given data images. In the proposed method to find out the occurrence of accident in the given video frame, mathematical features like average, median and mode are determined and used for classification purpose. The formula for calculating mean is given in Equation (1).

$$Mean\ \mu = \sum_{i=1}^{n} \frac{Xi}{n} \tag{1}$$

where X is the sum of all the values from 1 to n, n is the number of values.

2.6.2 Variance

Variance tests are used to calculate the dissimilarity within the given data set to identify the degree of variation from each item or each frame in the video data set. Variance is computed by taking the squared values of deviations and averaging the value from the mean. The value provides the grade of spread within the data set. The variance is proportional to the spread of deviation. The formula for calculating variance is given in Equation (2).

$$Variance\ S^2 = \sum_{i=1}^{n} (Xi - \mu)2/n \tag{2}$$

2.6.3 Standard Deviation

SD is the number representing the range of spread within the data set. SD shows the relationship with the mean values indicating the distribution of data with respect to mean. SD is calculated using the following steps:

1. First compute the mean of the data set values.
2. For every data point, distance from the mean is calculated and doubled.
3. Calculate the sum of all the values that are squared.
4. Finally divide the total by the number of data points.

The formula for calculating Standard Deviation is given in Equation (3).

$$S = \sqrt{S^2} \tag{3}$$

2.7 Hu Moments

Hu Moments are the shape feature vector calculated as a set of 7 numbers from H1 to H7 to identify the shape of the object from the outline in the given image dataset. Hu moments are the mean value of the pixel intensities of the given image that provides statistical measures of the image and moments are invariant to image transformations. Using these moments, shape is extracted, and similarity of the shape is identified from the image. Hu produced shape descriptors that are scale invariant from the symmetrical moments called raw moments. From the raw moments, central moments are intended and centroid localization with translation and scale invariances are calculated. The key points are the seven discrepancies calculated from rotational invariance. All the seven values describe the setting and locus of the shapes in the images. The basic calculations consist of translation, scale and rotational invariance values. They are:

1. Translation invariance:

$$M_{pq} = \sum_{x=0}^{n} \cdot \sum_{y=0}^{n} (x-x)^p \ (y- \ y)^q \, I(x,\ y) \tag{4}$$

In Equation (4) where I(x, y) gives basic 2D arithmetical moments of order (p + q) of the image, x^p, y^q gives moments basics, and p and q are weights of horizontal and vertical magnitudes.

2. Scale Invariance

$$N_{pq} = \ M_{pq}/M_{00}\ ^{1+p+q/2} \tag{5}$$

In Equation (5) where M_{00} is the total mass of the image.

3. Rotational Invariance

Hu defined the seven rotational invariants which are deliberated from above two formulas. They are:

$$h1 = \ \eta 20 \ + \ \eta 02 \tag{6}$$

$$h2 = \ (\eta 20 \ - \ \eta 02)^2 + \ 4\,(\eta 11)^2 \tag{7}$$

$$h3 = \ (\eta 30 \ - 3\,\eta 12)^2 + \ 3\,(\eta 03 \ - \ 3\eta 21)^2 \tag{8}$$

$$h4 = \ (\eta 30 \ - \ \eta 12)^2 + \ (\eta 03 \ + \ \eta 21)^2 \tag{9}$$

$$\begin{aligned} h5 = {} & (\eta 30 \ - \ \eta 12)\,(\eta 30 + \ \eta 12) \left[(\eta 30 + \ \eta 12)^2 - \ 3\,(\eta 03 \ + \ \eta 21)^2 \right] \\ & + (3\,\eta 21 \ - \ \eta 03)\,(\eta 03 \ + \ \eta 21) \left[3\,(\eta 30 \ + \ 3\eta 12)^2 - \ (\eta 03 \ + \ \eta 21)^2 \right] \end{aligned} \tag{10}$$

$$h6 = (\eta 20 - \eta 02)\left[(\eta 30 + \eta 12)^2 - 7\,(\eta 03 + \eta 21)^2\right] + 4\,\eta 11\,(\eta 30 + \eta 12)(\eta 03 + \eta 21) \tag{11}$$

$$\begin{aligned} h7 = {} & (3\eta 21 - \eta 03)(\eta 30 + \eta 12)\left[(\eta 30 + \eta 12)^2 - 3(\eta 03 + \eta 21)^2\right] \\ & + (\eta 30 - 3\eta 12)(\eta 03 + \eta 21)\left[3(\eta 30 + \eta 12)^2\ \ (\eta 03 + \eta 21)^2\right] \end{aligned} \tag{12}$$

Using the formulae of Equations (2), (3), (4), (5), (6), (7), (8), (9), (10), (11) and (12), Hu moment values are calculated, and seven features are derived from the images. The seven values are calculated for sample frames and displayed as Table 2 below.

Table 2. Hu moment sample values

Frames	H1	H2	H3	H4	H5	H6	H7
1	1.44	4.07	4.92	1.14	-7.38	-2.17	4.31
2	1.85	6.23	7.03	1.94	-2.27	-4.25	-1.16
3	1.66	3.55	5.15	1.12	-7.95	3.33	-3.24
4	1.44	2.03	9.45	3.66	2.08	2.78	5.42
5	1.44	4.07	4.92	1.14	-7.38	-2.17	4.31

2.8 Second Order Statistical measures

The second order statistical measures also called Gray Level Co-occurrence Matrix [GLCM] is the texture analysis method indicating the similarities with two adjacent pixels that have gray intensity, distance, and angle. The co-occurrence matrix is built by determining the intensity of the pixel and the occurrence in the image with respect to the contiguous pixels. While computing GLCM values from the matrix, many features are retrieved and six important structures like contrast, correlation, energy, homogeneity, dissimilarity, Angular Second Moment (ASM) are designed, and the formulas are given as follows:

1. Contrast — This texture measure provides the native differences in the image. The spatial frequency is computed with the top and bottom values of nearby pixels. The formula for calculating contrast is given in Equation (13).

$$\textstyle\sum_{i,j=0}^{N-1} P_{ij}(i-j)^2 \tag{13}$$

where i and j are adjacent pixel positions in the image.

2. Energy — Also called uniformity among images in the given video data set. It provides total of squared elements in GLCM. The formula used for computing is given in Equation (14).

$$\textstyle\sum_{i,j=0}^{N-1} P^2 I,J \tag{14}$$

3. Correlation — Usually measures the power of direct relationship between the data points in the image. By correlation the value of one data point can be identified using the other data point value. The formula is given in Equation (15).

$$\frac{\sum i \sum j(ij)p(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y} \tag{15}$$

In Equation (15) p(i,j) is the $(i,j)^{th}$ entry in the normalized GLCM, $\mu_x$and μ_y are the means of p(i,j), σ_x and σ_y are the standard deviations of p(i,j).

4. Homogeneity — Used for classification of texture in the image. The value is computed for each data point and similarity is determined by providing the value close to the adjacent points in the image. The formula is given in Equation (16).

$$\textstyle\sum_{i=1}^{n} (O_i - E_i)^2 / E_i \tag{16}$$

In Equation (16) where O_i is the observed value, E_i is the expected value.

5. ASM — To derive specified shape and texture accurately, this measure is used. Angular Second Moment produces homogeneity and contrast of the data points within the image. The formula used is given in Equation (17).

$$\textstyle\sum_i \cdot \sum_j P(i,j)^2 \tag{17}$$

6. Dissimilarity — This measure shows the variations that exist between the data points in the image. The formula is given in Equation (18).

$$\sum_{i=1}^{n} \left| X_{1(i)} - X_{2(i)} \right| / n \tag{18}$$

Using the formulae mentioned above, the values are calculated for sample images and the results are compared. The calculated values are given in the Table 3 as follows.

Table 3. GLCM sample values

Images	Contrast	Correlation	Energy	Homogeneity	ASM	Dissimilarity
1	1.68	9.02	5.84	9.30	3.42	1.44
2	1.63	9.16	6.13	9.32	3.76	1.39
3	3.32	8.56	3.64	8.43	1.33	3.15
4	3.25	8.92	3.89	8.63	1.51	2.81
5	1.68	9.02	5.84	9.30	3.42	1.44

Three standard feature extraction methods are discussed, and the features are used for classification models.

2.9 Classification Methods

In machine learning, the vital step is the classification of images to finalize whether they belong to the prescribed group or not. In the proposed model, the frames in the video shot are classified to check the occurrence of accident. Three popular methods are used for classifying the given data set, and they are Random Forest method, SVM and KNN methods. The results for three methods are derived for three set of frames namely 32, 64 and 128. Comparison of results is done for highest accuracy measurement.

2.9.1 Random Forest Method

The supervised learning algorithm mostly used in classification of images is the RF method also called bagging method since the result is the grouping of learning models. An ensemble of decision trees is the construction of forest used for training the data sets. This method is commonly called as bootstrap aggregation meaning finite set of data are used as repetitive samples and the final result is the average of all the decisions derived from all the models. The three key hyper parameters used in the model are node magnitude, length of the tree and total features used for sampling. The steps used for classification are:

1. First the data set is divided into training and testing phase with 80% used for training and remaining for testing purpose.
2. The decision tree is built with predominant features and data points selected from the video set.
3. Each tree will produce one output and all the outputs are considered based on voting system and decision with majority is taken as the final output.

The hyperparameters for the Random Forest algorithm used in video set classification:
No of estimators (200): The number of decision trees built by the algorithm.
Maximum depth (150): The maximum levels each decision tree can have.
Verbose (1): The level of information printed during training.

2.9.2 SVM Classification Model

Support Vector Machine is the popular supervised machine learning model used for classification problems. The model basically converts the image into data points distributed in multidimensional space with a hyper plane that divides the data points into clusters of same value. The important notions in SVM are:

1. Support Vectors – The data points nearby the hyper plane are called support vectors. They are clearly depicted in the above diagram in two different colours.
2. Hyper plane – The decision line breaking the group of data points into various clusters is the decision or hyper plane. There are both positive and negative hyper plane.
3. Margin – Indicated as maximum margin in the figure is the distance between the two hyper planes with adjacent points belonging to two different classes. Larger the margin high is the performance.

The main function of SVM model is to classify the given frame whether accident occurred or not using the features provided. For this purpose, the frame is converted into data points which are divided into two classes based on the hyper plane. For this purpose, first step hyper planes are generated to divide the classes in the possible way. Next step is the selection of the hyper plane that splits the classes accurately.

2.9.3 KNN Classification Model

This classification model is supervised machine learning classifier which is non- parametric by predicting the classes approximately based on the surrounding priory collected data to label the new data. Following are the steps used for classification of given video frames into two classes to identify whether accident occurred in the given frame. They are:

(i) The main idea of KNN algorithm is the similarity diagnosed between the new data points with the already categorised points and assigns the new point to the class based on the resemblance.

(ii) The model for classification of the proposed data set is created by selecting the number of neighbours say K.

(iii) The distance between the new data points and the assigned classes are calculated using Euclidean distance method. The formula is given in Equation (19).

$$D(x,y) = \sqrt{\sum_{i=1}^{n} (y-x)2} \tag{19}$$

(iv) Next calculate the nearest neighbours and make the count of the data points for each class.

(v) The crucial step is the assignment of new data point based on the similarity between the adjacent points based on the formula and assigns the points to the class matching with the contiguous data point.

Based on the above algorithm the given data sets are categorized to predict the occurrence of accident in the given frame of the video. Thus, three classification methods are discussed for the accident event and their results are computed and compared for three set of frames.

3 Results and Discussion

The videos are retrieved from the data base which is pre-processed, and features are extracted for classification purpose. For classification of video frames, three set of frames are collected and trained using three Machine Learning (ML) classification models. Accuracy is attained and checked for three set of frames and discussed in the following section.

(i) First Set of Frames

The initial set of frames contains 32 number slides which are trained using the machine learning model. The result is calculated given as Table 4.

Table 4. First set frame result analysis

FPS	Algorithm	Precision	Recall	F1 Score	Accuracy in (%)
32	Random Forest	0.90	0.90	0.89	90
32	SVM	0.08	0.20	0.10	20
32	KNN	0.50	0.50	0.50	50

For 32 FPS, Random Forest outperforms both SVM and KNN across all metrics (Precision, Recall, F1 Score, and Accuracy). SVM performs poorly with only 20% accuracy and an F1 Score of 0.10. KNN performs moderately with 50% accuracy and an F1 Score of 0.50.

(ii) Second Set of Frames

The next set of frames contains 64 slides in the frame, and they are trained using the standard machine learning models. The result is given as Table 5.

Table 5. Second set frame result analysis

FPS	Algorithm	Precision	Recall	F1 Score	Accuracy in (%)
64	Random Forest	0.92	0.92	0.92	92
64	SVM	0.10	0.25	0.13	25
64	KNN	0.52	0.53	0.52	53

For 64 FPS, Random Forest outperforms both SVM and KNN across all metrics (Precision, Recall, F1 Score, and Accuracy). It has a Precision, Recall, and Accuracy of 92%, and an F1 Score of 0.92. SVM performs poorly with only 25% accuracy and an

F1 Score of 0.13. KNN performs moderately with 53% accuracy and an F1 Score of 0.52.

(iii) Third Set of Frames

The last set of frames contains 128 slides and best accuracy is derived for this set of frames. The result is given as Table 6.

Table 6. Third set frame result analysis

FPS	Algorithm	Precision	Recall	F1 Score	Accuracy in (%)
128	Random Forest	0.96	0.96	0.96	96
128	SVM	0.12	0.27	0.15	27
128	KNN	0.59	0.61	0.59	60

For 128 FPS, Random Forest outperforms both SVM and KNN across all metrics (Precision, Recall, F1 Score, and Accuracy). It has a Precision, Recall, and Accuracy of 96%, and an F1 Score of 0.96. SVM performs poorly with only 27% accuracy and an F1 Score of 0.15. KNN performs moderately with 60% accuracy and an F1 Score of 0.59.

The UCF dataset is trained for all three different FPS collection and the result analysis is given in tabular form above. Figure 2 shows the accuracy of various ML algorithms with different frames per second.

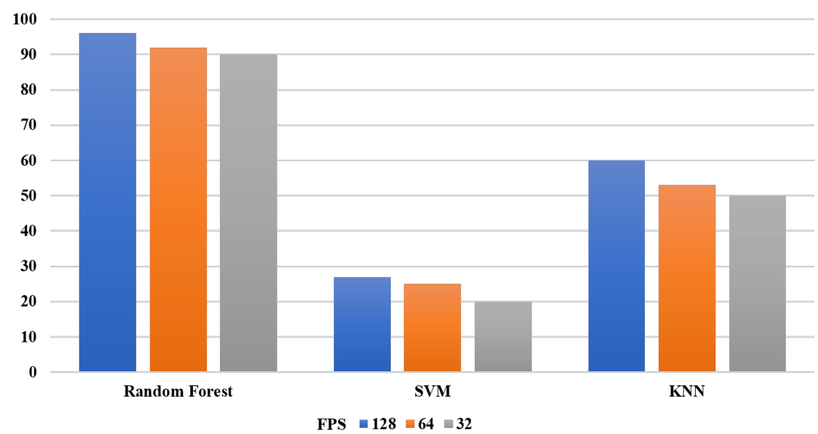

Fig 2. Accuracy of various ML algorithms

The key insight from the Tables 4, 5 and 6 and Figure 2 shows that the Random Forest is the most effective algorithm among the three ML algorithms for performing this particular task.

Table 7. Comparative Study

Reference	Method	Key Findings	Accuracy
Shakil et al [12]	ML models (RF, DJ, AdaBoost, XGBoost, L-GBM, CatBoost)	Predicts road accident severity	81.45% (RF)
Josephinshermila et al [2]	AI and machine learning algorithms	Traffic accident detection method for connected and automated transport systems using grid-based parameter extracting and SVC-based traffic state classification	87.72% (SVM)
Krioudj et al [10]	XGBoost	Predicts road accidents	94.31%
Proposed model	automating accident detection System	Predict the road accidents in real-time and Sends information for emergency response.	96.02% (RF)

Table 7 provides a concise summary of each study, the methods used, their key findings, and the accuracy of their models. The studies by Shakil et al [12], Josephinshermila et al [2] and Krioudj et al [10] are particularly relevant as they also use machine learning models and provide accuracy metrics, which can be directly compared with the accuracy of the proposed model, and it performs better than previous accident detection system. This might entail examining research that has employed identical or comparable machine learning algorithms for detecting accidents. Differences in factors could be due to variations in the data sets that are used for training and testing, and also the specific implementation of the algorithms.

4 Conclusion

The proposed model represents a significant advancement in accident detection and response, harnessing the power of machine learning and specifically the Random Forest algorithm. By training and testing on recorded video datasets at varying frame rates, the model achieves high accuracy in accident detection, particularly at 128 FPS. Once an accident is detected in real-time videos, the model can automatically alert various services, including ambulance, control room, mechanics, and close friends, facilitating immediate recovery efforts. This model not only holds great promise in reducing the fatal effects of accidents and improving road safety but also opens up possibilities for future enhancements. Future work could explore the application of this model.

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