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An Optimized Deep Learning Framework For Pothole Detection

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Abstract

Pothole detection plays a crucial role in preventing road accidents and is effective in establishing road maintenance and safety. Although various pothole detection models are designed to accurately identify the pothole based on road images, they face issues in accuracy and hyperparameter tuning. The presented research work concentrates on developing a novel optimized deep learning model for the accurate prediction of potholes on the road infrastructure using the recurrent neural network (RNN) and grey wolf optimization (GWO). Initially, the road images are collected and pre-processed. The pre-processing includes the removal of noises, image resizing, etc., to improve the image quality. Further, texture-based feature extraction was employed to extract the most relevant features from the pre-processed image. Then, the RNN architecture was trained using the extracted features to learn the interconnections between the image features and pothole detection. In addition, the GWO fitness solution was integrated into the classification module to tune and optimize the RNN hyperparameters, which increases the detection performances such as accuracy, and reduces the loss function. Finally, the presented model was evaluated with the publically available road image detection database and the outcomes are determined. The performance assessment demonstrates that the designed model attained greater accuracy of 98.76%, and a loss function of 0.06. Furthermore, a comparative assessment was performed with existing methods to evaluate the effectiveness of the proposed model.

Keywords: Pothole detection, Recurrent neural network, Grey wolf optimization, Texture-based feature extraction

1. INTRODUCTION

The growing demand for vehicles worldwide considers the factors like accident reduction, traffic smoothening, and road safety actions to ensure safe transportation [1]. In India, the road infrastructure is the major source of transportation, that is around 90% of the population in the country prefers to travel by road transportation [2]. In addition, it is important to notice that because of the huge population, Indian roadways are constructed in congested and narrow ways with low maintenance and surface quality [3]. A recent study conducted in India reports that in the year 2021 around sixty thousand people died while driving vehicles because of the cracks in the roads [4]. Therefore, proper design and maintenance of the road infrastructure are significant to minimize accidents [5]. Moreover, the earlier detection of road circumstances minimizes the economic losses faced by transportation agencies and enables them to make decision actions in providing road quality [6]. Presently, many kinds of research are carried out regarding the assessment of road conditions. Nowadays, most of the road infrastructure includes a speed breaker, which controls the vehicle speed and reduces road accidents. In some cases, the speed breakers are not even and are constructed at dissimilar heights [7]. This instance leads to pothole formation, which is mainly because of the continuous movement of vehicles, heavy rainfall, etc., and causes damage to human lives [8]. Moreover, it leads to financial losses for the government's transport agencies.

Hence, monitoring the road infrastructure is important for the detection of potholes [9]. The early identification of potholes enables a better travel experience for the passengers and prevents accidents [10]. Although various types of research were performed for the early identification of potholes, the number of potholes is increasing day by day because of the worsening weather conditions, wide usage of roads, and transport of heavy loads on roads [11]. The pothole represents a structural failure, which occurs in roads due to periodic traffic over the region for a long time, heavy rainfall in the region, etc., [12]. It is the form of a bowl-shaped area, which occurs in the pavement region with a minimum depth of 150mm [13]. The major factors that influence potholes are the aging of road infrastructure, poor road maintenance, heavy traffic circumstances, heavy rainfall, and poor drainage [14]. Subsequently, the potholes occur because of internal and external causes [15]. The internal conditions include depletion of the pavement materials, heavy snowfall, durability, and heavy rainfall [16].

On the other hand, the external factors include poor drainage, poor construction, and maintenance. The analysis of these factors enables accurate and effective identification of potholes in the road surface [17]. Finally, the data regarding the detected pothole is transferred automatically to the central server using automatic machine algorithms [18]. This process enables the passengers to access information about potholes at any place and time in a non-payable manner. Although various pothole identification models including the convolutional neural networks, deep learning framework YOLO (you only look once), EfficientNet, etc., are developed for the identification of surface irregularities on roads, they cannot provide accurate detection. This research work concentrates on developing an optimized deep-learning framework for the detection of potholes on road surfaces.

The arrangement of the research article is sequenced as follows, the recent research literature related to the presented work is described in section 2, the proposed methodology was explained in section 3, the results of the developed model were analyzed in section 4, and the research conclusion is described in section 5.

2. RELATED WORKS

A few recent literature works associated with the presented work are detailed below,

Potholes define the tear in the road surface causing discomfort to passengers and sometimes leading to vehicle accidents. D RohitRajan*et al* [19] proposed a deep learning (DL) framework to detect the potholes on the road surface, thereby minimizing the number of accidents across roads around the world. This framework utilizes the Yolo approach for the identification of potholes. This model was tested with the real-time road database collected from the camera installed in the moving vehicles. However, this framework demands a large amount of labeled data for training purposes, which is time-consuming.

IlaiahKavati*et al* [20] developed a Mask Regional-assisted Convolutional Neural Network (R-CNN) framework to identify the potholes in the images. This model overcomes the drawback such as time complexity, and high experimental cost induced by the manual reporting and conventional 3-dimensional reconstruction approach. The designed model was trained and evaluated with the MS COCO database. However, this model generates more false positives and negatives in the detection phase.

The manual reporting methodology for the detection of potholes is a complex task and it involves tedious processes and demands a large workforce. To resolve this issue, Rohitaa R *et al* [21] introduced a DL-based automatic pothole identification approach. This model incorporates the DL algorithms like CNN, Mask R-CNN, and Yolo version 3. These models are trained and tested with the publically available pothole database and the results are analyzed. But optimization and fine-tuning of hyperparameters in the combined multiple DL models is complex.

SurekhaArjapure*et al* [22] designed a DL-based Mask R-CNN model to identify the potholes efficiently. Initially, the database was manually collected from the Mumbai city highways. This database was annotated using the VGG Image Annotator tool and then the pothole region was detected using the Mask R-CNN approach. The designed framework was modeled in the Python software and it obtained 90% of detection accuracy. However, this method often faces generalization issues and is prone to overfitting.

The prediction of potholes plays a crucial role in road monitoring and maintenance. The deficiency of effective detection mechanisms and mapping of potholes motivates to design of an end-to-end framework to provide real-time assessment of road surfaces. SusmitaPatra*et al* [23] introduced a novel approach using the CNN algorithm to predict the potholes accurately. This methodology creates a real-time pothole mapping using the Google-assisted application-programming interface. Finally, the performances are compared with the existing DL framework. But this model is prone to error and is time-consuming compared to other approaches.

Sang-Yum Lee *et al* [24] proposed a computer vision-assisted approach using the image fragmentation algorithm for predicting the potholes in the road surface. This method was evaluated with the pothole images collected from the urban roads. In addition, it measures the damage ratio of the road surface. The implementation results ensure that the proposed model is accurate in detecting potholes on road surfaces. However, the accuracy of this design relies on the quality of the collected images and cannot handle the noisy image.

An effective pothole prediction plays a significant role in road management and transportation system by reducing the number of road accidents. MallikarjunAnandhalli*et al* [25] presented a technique using the sequential CNN algorithm and anchor-assisted Yolo version 3 algorithms. The model efficiency was examined in terms of accuracy, precision, and resource consumption. However, this model lacks interpretability and faces difficulty in hyperparameter tuning.

3. PROPOSED METHODOLOGY

A hybrid optimized deep learning framework was proposed in this article to predict the pothole based on the road images. This method combines the recurrent neural network (RNN) and the grey wolf optimization (GWO) algorithms for accurately predicting the pothole. The proposed framework includes four major phases namely, data collection, image pre-processing, feature extraction, and classification. Initially, the photographic road images are collected and fed into the system. The input images undergo pre-processing mechanism, which increases the quality of the images. The pre-processing step involves noise filtering, image contrast enhancement, image resizing, and greyscale conversion. Further, texture-based feature engineering was performed to extract the most relevant features from the pre-processed image. In the classification module, the RNN architecture was integrated with the grey wolf optimizer to provide accurate pothole detection. The proposed model architecture is described in Fig 1.

3.1 Data collection and image quality enhancement

Initially, the photographic road images are gathered from the publically available pothole detection database and fed into the system. The collected database contains images labeled pothole and non-pothole instances. The dataset representation is expressed in Eqn. (1).

$$P_{Ds} = \{P_{I1}, P_{I2}, P_{I3}, P_{I4}, ...P_{Iz}\} \qquad (1)$$

Where P_{Ds} indicates the collected database, P_I defines the labeled pothole or non-pothole images, and z refers to the total number of images present in the database. These collected images may contain noise features in it. Therefore, these images are pre-processed to enhance the quality, which increases the detection accuracy.

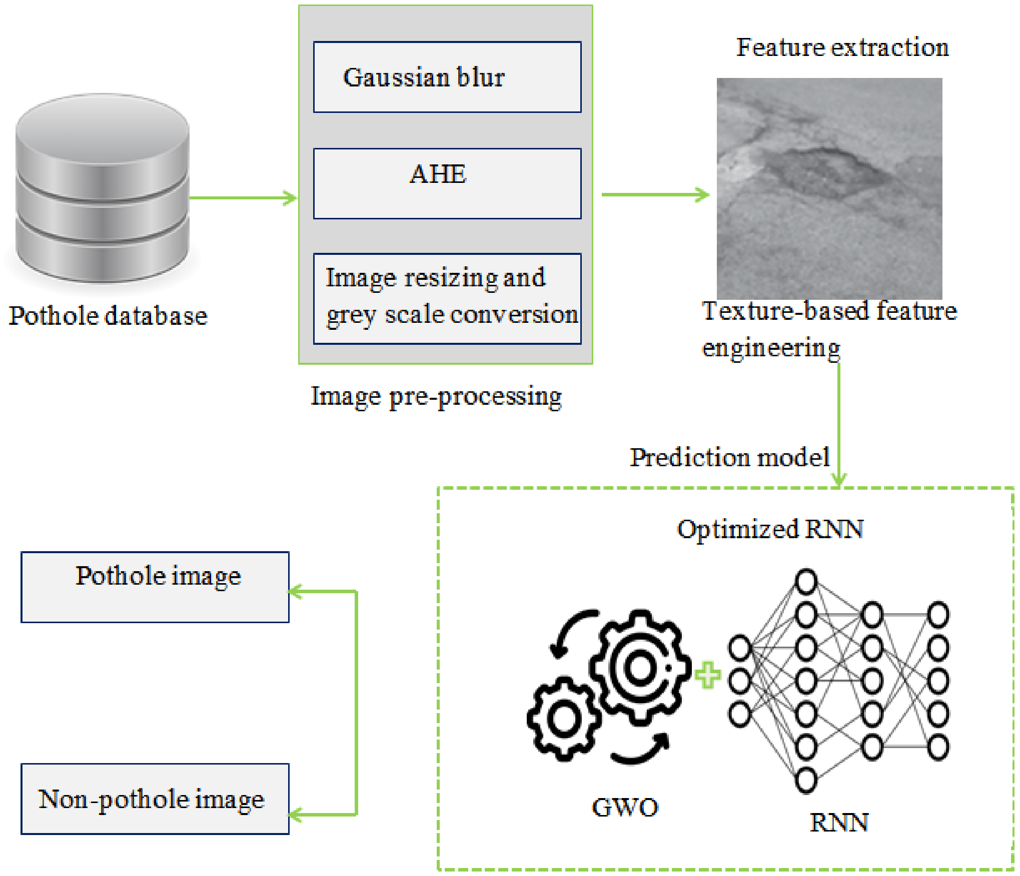

Fig. 1 Proposed GWO-RNN Framework

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In the proposed work, the typical Gaussian blur technique was applied to eliminate the noises present in the images. The Gaussian blur is a smoothing approach, which minimizes the noises present in the images by convolving the image with a Gaussian kernel. The Gaussian kernel defines the matrix, which allocates more weight to the center pixel and slowly minimizes the weight to the pixel away from the center. In the kernel window, the convolution function calculates the weighted average of the pixel intensities and substitutes the center pixel with the calculated average value. The mathematical derivation for the Gaussian blur function is expressed in Eqn. (2).

$$P_I(a,b) = \sum\sum\left(P_I(a',b') * \chi(a-a',b-b')\right) \quad (2)$$

Here, $P_I(a,b)$ defines the pixel intensity at position (a,b) in the input image, $P_I(a',b')$ represents the pixel intensity at position (a',b') in the original input image, and χ represents the Gaussian kernel value. This makes the images smoother and enhances their clarity. Further, the image contrast was improved using the adaptive histogram equalization (AHE) approach to increase the visibility of the pothole attributes. The equation for AHE is expressed in Eqn. (3).

$$P_I^{'}(a,b) = C_{dfl}\left(P_I(a,b) * (\delta - 1)\right) \quad (3)$$

Where $P_I^{'}(a,b)$ refers to the improved pixel intensity at the position (a,b), C_{dfl} indicates the local cumulative distribution function, and δ defines the possible intensity levels in the input image. This approach modifies the intensity distribution within local regions and improves image contrast. Then, the images are resized to a consistent resolution to standardize the input size of the images present in the database. Further, the resized images are converted to grayscale to minimize the computational time and this simplifies the image analysis. These processes increase the quality of the image and make the detection process simple.

3.2 Feature extraction

After image quality improvement, feature extraction was performed to extract the most relevant features for pothole detection. Before feature extraction, a sequence of attributes is selected based on their relevance to pothole detection. In the proposed work, texture-based feature extraction (Haralick features) was utilized to extract the most relevant features for pothole detection from the pre-processed image. The Haralick features-texture analysis is a statistical approach, which captures various textural properties based on the gray-level co-occurrence matrix (GLCM). The GLCM defines the spatial interconnections between the pixel pairs in an image and offers information about texture patterns. The GLCM is a 2D matrix, which captures the frequency of occurrence of various combinations of gray-level values at specific pixel pairs. It is calculated by evaluating a specific distance and angle between the pixel pairs and counting the occurrences of each gray-level combination. In this process, the features including the energy, contrast, entropy, correlations, and homogeneity are captured from the GLCM. These attributes capture various characteristics of texture and offer valuable information for pothole detection. These extracted features are fed as inputs to the pothole detection framework for prediction purposes.

3.3 Optimized RNN for pothole detection

The designed GWObRNN framework integrates the benefits of both GWO and RNN approaches to detect the pothole from the road images. Initially, the RNN architecture was designed to classify the input image as either pothole or non-pothole. The RNN accepts the extracted features from the texture-based feature engineering (Haralick features) as inputs to learning the temporal patterns in the input image. The RNN input representation is expressed in Eqn. (4).

$$I_P[R_{NN}] = [F_1, F_2, F_3, ..., F_W] \quad (4)$$

Here, $I_P[R_{NN}]$ defines the input of RNN architecture, F refers to the input features, and W indicates the number of attributes given as inputs. The RNN is a type of deep learning architecture, which contains multiple Long Short-Term Memory (LSTM) cells or Gated Recurrent Unit (GRU) cells to learn the temporal patterns in the input sequence. These layers process the input features sequentially, one feature at a time. At each time step, the LSTM cells update the hidden states based on the current input

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feature and the previous hidden state. The hidden states capture the learned data from previous time steps and serve as the memory of the network. This process continues and the final hidden state of the RNN is passed through a fully connected layer followed by an activation function to generate the output. The final hidden state passed through the fully connected layer followed by the sigmoid activation function is expressed in Eqn. (5).

$$X = q.\ H(F) + Bw \tag{5}$$

Here X defines the weighted sum of the final hidden state $H(F)$, q denotes the weight matrix, and Bw represents the bias vector. The output probability calculation is expressed in Eqn. (6).

$$Y_{op} = \gamma(X) \tag{6}$$

Here Y_{op} defines the output probability range from 0 to 1, and γ indicates the sigmoid activation function. The sigmoid activation function is represented in Eqn. (7).

$$\gamma(F) = \frac{1}{(1 + \exp(-F))} \tag{7}$$

The final classification was made by applying a threshold value to the output probability. If the output probability is greater than the threshold value, it is classified as a pothole, and if the output probability is less than the threshold value, it is classified as a non-pothole. It is expressed mathematically in Eqn. (8).

$$P_D = \begin{cases} if(Y_{op} > T_d);\ Pothole \\ if(Y_{op} < T_d);\ Non-pothole \end{cases} \tag{8}$$

Here P_D refers to the pothole detection function, and T_d denotes the threshold value, it set as 0.6. Thus, the RNN system learns the interconnection between the input and output and classifies the image as pothole or non-pothole. In this training process, the loss function was introduced to estimate the deviation between the actual and predicted labels. Typically, the loss function was calculated using the mean squared error. The loss function was minimized by optimizing the hyperparameters of the RNN model. In the designed framework, the GWO algorithm was utilized to optimize and tune the hyperparameters including learning rate, batch size, or number of hidden units. The GWO is a meta-heuristic optimization approach, which mimics the hunting characteristics of grey wolves. The GWO approach works by the initialization of the grey wolf population, in which each grey wolf indicates the potential solution in the hyperparameter space. The initialization of the grey wolf population is expressed in Eqn. (9).

$$G_w = \{g_{w1}, g_{w2}, g_{w3}, \ldots\ldots, g_{wk}\} \tag{9}$$

Here, G_w denotes the grey wolf population, g_w indicates the position of the grey wolves in the population space, and k denotes the population size. In the proposed method, the GWO approach explores the hyperparameter space and modifies the RNN parameters to enhance the system's performance. In the designed model, the GWO fitness function aims to improve the performance of the RNN model by adjusting the hyperparameters. For each set of hyperparameters, the fitness solution evaluates the RNN performances. At iteration, the position of the grey wolves is updated based on their hunting behavior. First, the model searches for the top three sets of positions of the grey wolves α, β and γ (hyperparameters) and then evaluate the fitness solution for these hyperparameters' sequence. Based on the fitness values, α, β γ positions are updated to select the best hyperparameter sequence. This process is repeated until the convergence conditions are met (high accuracy and low loss). The integration of the GWO approach enables to exploration and exploit the hyperparameter space and helps to improve the RNN performance by iteratively updating the position of the grey wolves optimally. The algorithm leverages the population-based

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search mechanism of grey wolves to iteratively update and refine the hyperparameter values, leading to improved results. Thus, the proposed hybrid model provides effective pothole detection with greater accuracy.

4. RESULTS ANALYSIS

In this module, the performances of the proposed framework were analyzed by implementing it in MATLAB software version R2020a, running in Windows 10 Operating System (OS). The results are analyzed in terms of accuracy, recall, f-measure, and precision.

4.1 Dataset description

To evaluate the proposed framework, a publically available pothole dataset was collected from the Kaggle site. This dataset contains both normal (non-pothole) images and pothole images. The normal images include smooth road images from various viewpoints. The potholes include images of roads with holes. This database contains a total of 329 images combining both pothole and non-pothole images. The database was split into ratios of 75% and 25% for training and validation purposes and the convergence of the proposed model was evaluated in terms of accuracy, and losses.

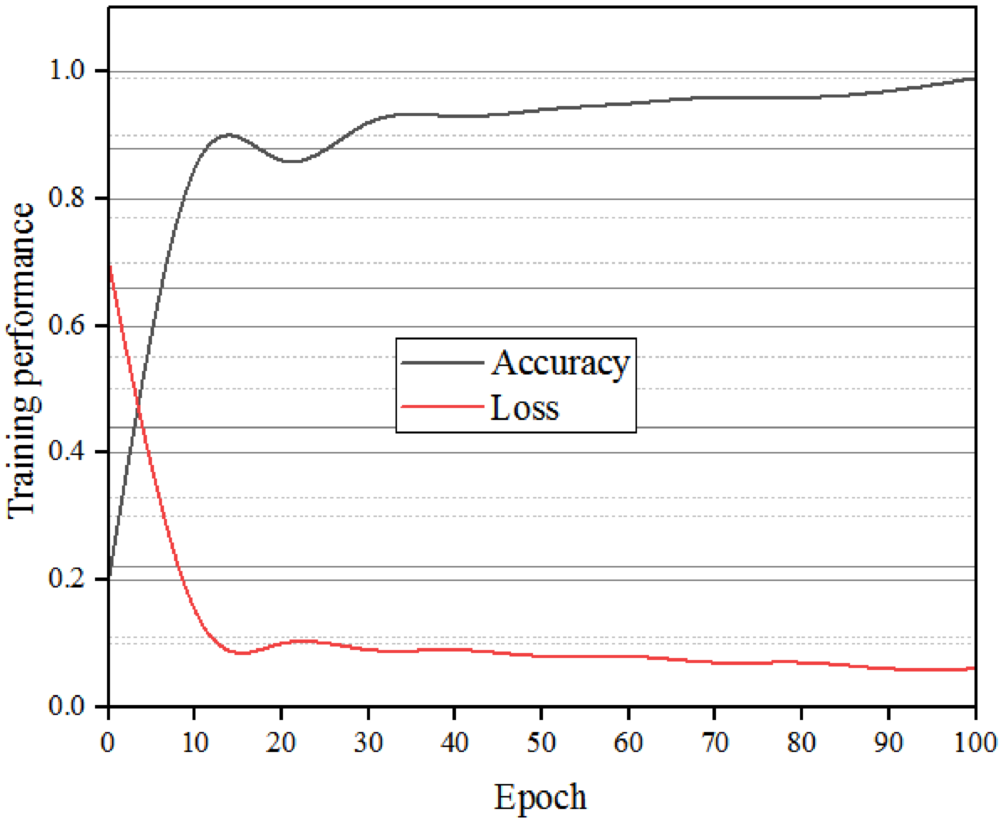

Fig. 2 Training set performance

In pothole detection, the training accuracy defines the rate of correct prediction of pothole instances in the training dataset. It measures how quickly the designed model learns the interconnections between the input and the desired features. The training accuracy was evaluated relative to the iterations. The increase in training accuracy over the epochs defines the effectiveness of the proposed model and it attained an approximate accuracy of 0.99. On the other hand, the training loss was measured to quantify the deviation between the actual and predicted results. It defines the mismatch between the detected pothole labels and the actual pothole labels. The designed model incurred a very low loss rate of 0.06, which demonstrates that the variation between the actual and predicted label is very minimum. The training and validation set performances are illustrated in Fig 2, and 3.

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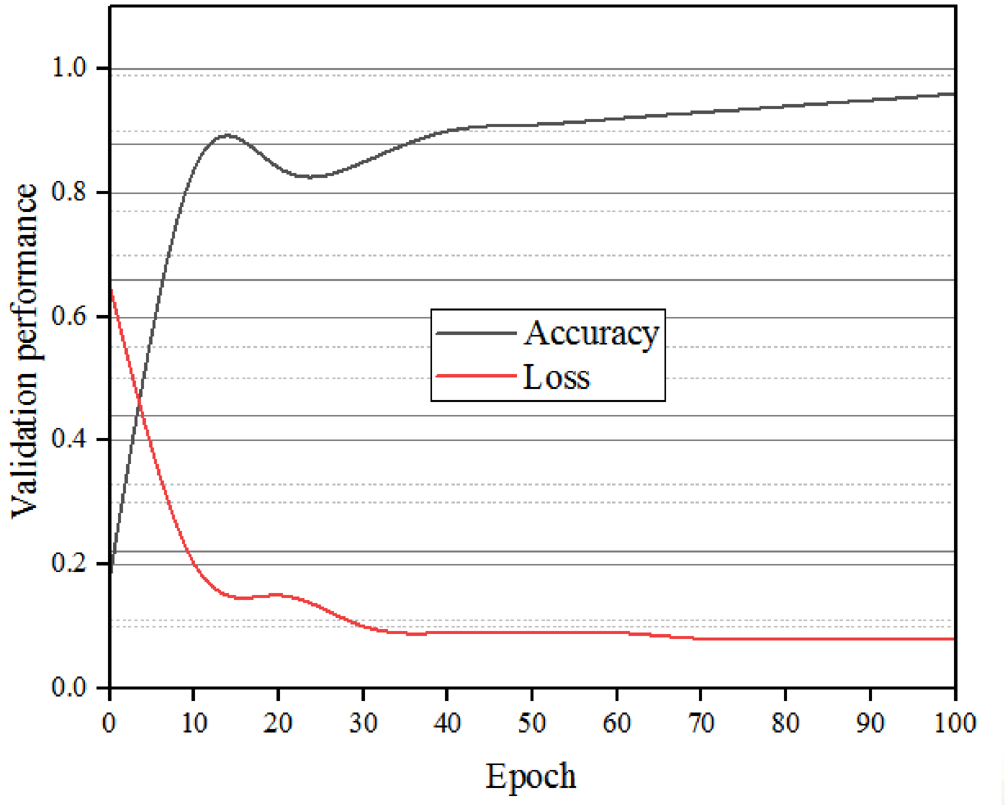

Fig. 3 Validation set performance

Similar to training accuracy, validation accuracy defines the rate at which the proposed model performs in the validation dataset. In addition, it determines how the proposed model generalizes pothole detection to unseen data. The validation loss defines the error between the actual and predicted labels in the validation data. It evaluates how well the proposed model makes accurate pothole detection on unseen data. These metrics enable the evaluation of the system's performance and its ability to prevent overfitting issues.

4.2 Performance evaluation

In this section, the performances of the proposed framework were analyzed and validated with existing techniques. The outcomes of the model were examined in terms of accuracy, precision, recall, and f-measure. The existing techniques include CNN [26], Mask R-CNN [20], Convolutional Neural Network-based Modified Aquilla Optimization (CNN-MAO) [27], Improved Deep Convolutional Neural Network (IDCNN) [28], and DL-based YOLO [29].

4.2.1 Accuracy

The term accuracy quantifies the overall correctness of the proposed model by evaluating the proportion of correct detected potholes and non-pothole areas to the total number of instances. The formula for the calculation of the accuracy is expressed in Eqn. (10).

$$Acc = \left(\frac{m^{+} + m^{-}}{m^{+} + m^{-} + n^{+} + n^{-}} \right) \tag{10}$$

Here Acc denotes the system accuracy, m^{+}, m^{-}, n^{+}, and n^{-} refers to the true-positive, true-negative, false-positive, and false-negative.

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4.2.2 Precision

Precision evaluates the proportion of correctly detected potholes out of all instances identified as potholes, evaluating the proposed model's capability to prevent false positives and it is mathematically evaluated in Eqn. (11).

$$Pcs = \left(\frac{m^+}{m^+ + n^+} \right) \tag{12}$$

Here, Pcs defines the precision.

4.2.3 Recall

The recall represents the proportion of correctly identified potholes out of all actual potholes in the database, evaluating the designed approach's ability to identify potholes and it is equated in Eqn. ().

$$Rcl = \left(\frac{m^+}{m^+ + n^-} \right) \tag{13}$$

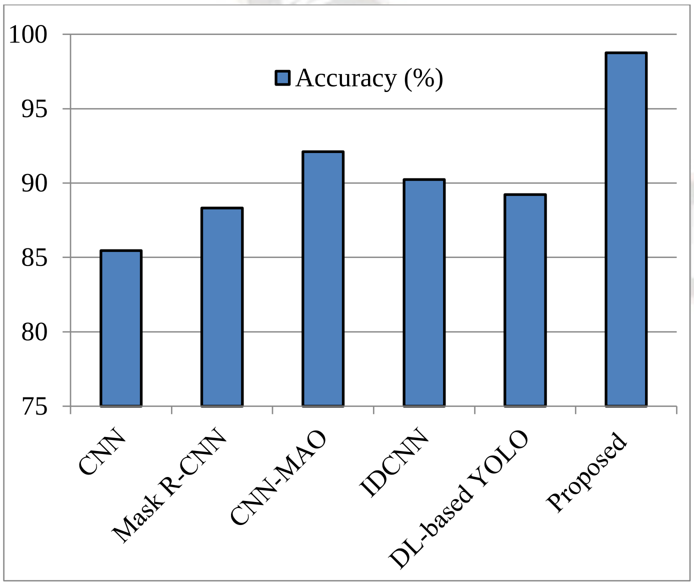
Where Rcl denotes the recall.

4.2.4 F-measure

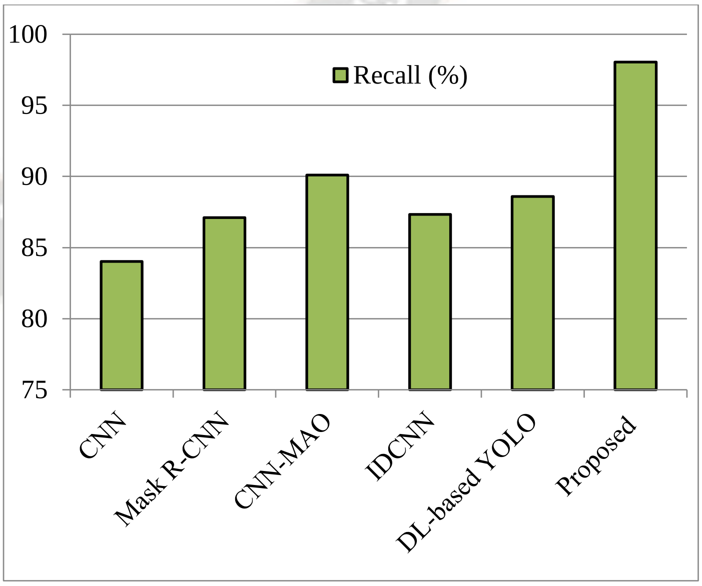
F-measure refers to the harmonic mean of precision and recall performances, indicating a balanced outcome of the designed model outcomes. It combines both precision and recalls into a single value, evaluating the overall efficiency of the designed framework in pothole detection. It is represented in Eqn. (14).

$$Fm = 2\left(\frac{Pcs * Rcl}{Pcs + Rcl} \right) \tag{14}$$

Where Fm represents the f-measure.



(a) Accuracy



(b) Recall

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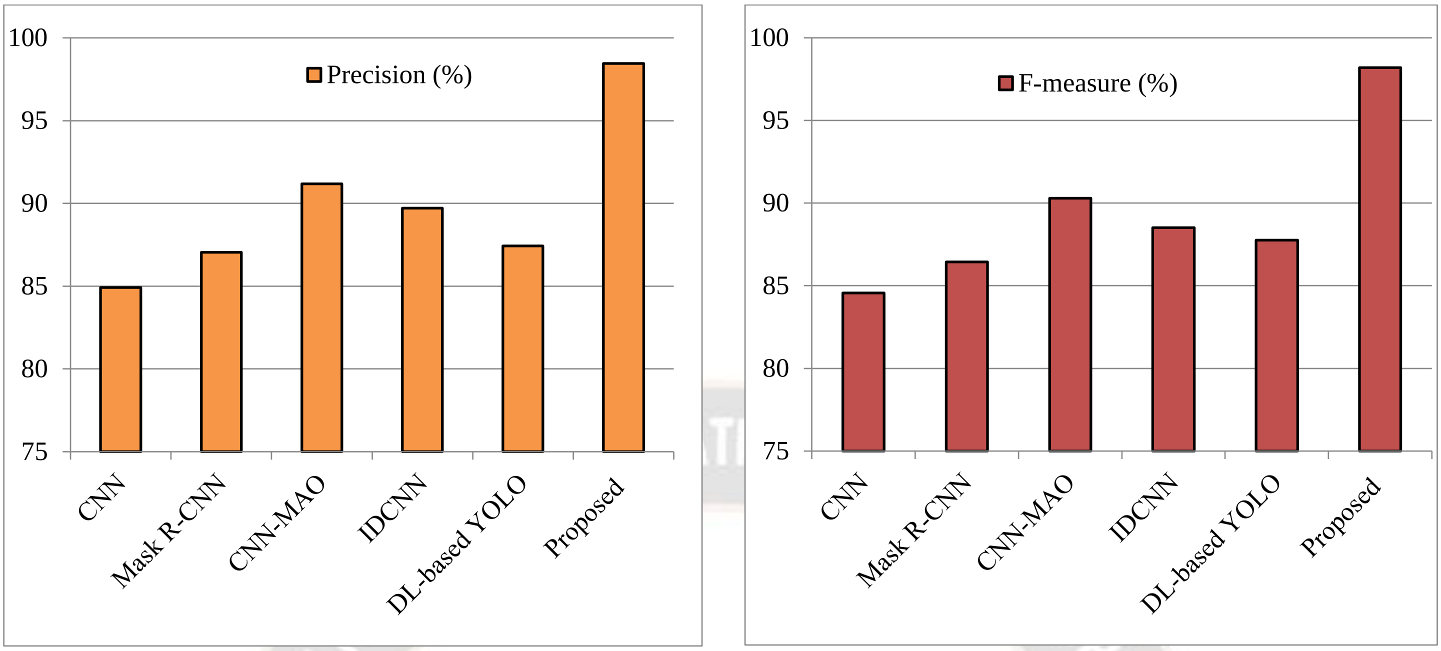

(c) Precision **(d) F-measure**

Fig. 4 Performance evaluation: (a) accuracy, (b) Recall, (c) Precision, (d) F-measure

The performance evaluation and comparison are examined in Fig 4. The evaluation of the developed model results with these existing methods demonstrates the efficiency of the proposed model. Here, the outcomes are compared with the conventional potholes prediction frameworks such as CNN, Mask R-CNN, CNN-MAO, IDCNN, and DL-based YOLO. The accuracy obtained by these models in pothole prediction is 85.46%, 88.32%, 92.10%, 90.23%, and 89.23%, respectively. Similarly, the precision rate earned by these designs is 84.92%, 87.05%, 91.19%, 89.71%, and 87.43%, respectively. The recall percentage attained by these models is 84.02%, 87.11%, 90.09%, 87.32%, and 88.60%, respectively.

Table 1 Statistical comparative assessment

Methods	Accuracy (%)	Recall (%)	Precision (%)	F-measure (%)
CNN	85.46	84.02	84.92	84.57
Mask R-CNN	88.32	87.11	87.05	86.44
CNN-MAO	92.10	90.09	91.19	90.29
IDCNN	90.23	87.32	89.71	88.52
DL-based YOLO	89.23	88.60	87.43	87.75
Proposed	98.76	98.05	98.45	98.20

Finally, the f-measure gained by these frameworks is 84.57%, 86.44%, 90.29%, 88.52%, and 87.75%, respectively. From the analysis, it is clear that the designed detection model achieved greater accuracy of 98.76%, 98.05% recall, 98.45% precision, and 98.20% f-measure, which is greater than the conventional pothole prediction methodologies. Table 1 tabulates the statistical analysis of comparative analysis.

5. CONCLUSION

In this article, a hybrid GWO-RNN framework was designed to detect potholes based on road images. In the designed model, the RNN model captures the temporal interconnections and dependencies in the input road images and predicts the pothole accurately. The LSTM cells in the RNN effectively learn the sequential data in the extracted features classifies the pothole and non-pothole images. The incorporation of GWO in the classification module optimizes the RNN hyperparameters by exploring the hyperparameter space using the population-based search algorithm. Thus, the integration of the GWO model improves the RNN classification performance and reduces the loss function. The designed framework was trained and validated with the road damage detection database. Finally, an intensive comparative analysis was performed with the existing techniques such as CNN, Mask R-CNN, CNN-MAO, IDCNN, and DL-based YOLO, and the performance enhancement score was estimated. It is noticed that in the proposed framework the performances such as accuracy, precision, recall, and f-measure are improved by 6.66%, 7.26%, 7.96%, and 7.91%, respectively. From the comprehensive analysis of the proposed model, it is proven that the proposed model is accurate in the detection of potholes.

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