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AI-Powered Retinal Disease Detection System for Diabetic Retinopathy Screening

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***Abstract*—A retinal condition linked to diabetes, diabetic retinopathy is one of the main causes of blindness in the elderly population. Early identification using blood vessel analysis is essential for avoiding vision loss since it is generally asymptomatic in its early stages and is characterized by progressive damage to retinal blood vessels that may leak or burst, impairing vision. An intelligent deep learning framework based on Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models is developed and compared with conventional machine learning and deep learning techniques like SVM, XGBoost, ResNet50, and DenseNet201 in this study, which proposes an automatic diabetic retinopathy detection system using color fundus images. To enhance the image and extract features, preprocessing methods such cropping, denoising, histogram equalization, scaling, data augmentation, and normalization are used to the APTOS 2019 dataset. According to experimental data, the GRU model performs competitively with 98.36% accuracy, 97.62% precision, 99.19% recall, and 98.40% F1-score, while the suggested LSTM model attains the maximum performance with 98.64% accuracy (ACC), 98.14% precision (PRE), 99.19% recall (REC), and 98.66% F1-score (F1). The proposed sequential deep learning models outperform the baseline models in terms of classification ACC and reliability for automated detection of DR and early clinical screening support.**

Keywords*—Macular Edema, Artificial Intelligence, Machine Learning, Deep Learning, Retinal Imaging, Retinopathy, Maculopathy, Image Classification, Image Preprocessing, Color Spaces, Diabetic Retinopathy.

I. INTRODUCTION

Diabetic retinopathy screening is crucial for preventing vision loss and enhancing healthcare results for diabetic patients by detecting retinal diseases early and accurately [1]. Diabetes mellitus is a chronic metabolic disorder with persistently elevated blood glucose levels that can lead to severe complications that involve multiple organs of the body [2][3]. Diabetic retinopathy (DR) is one microvascular complication among them and is a major cause of vision loss and preventable blindness in the working-age population globally [4]. With a diabetic population increasing at a rapid pace all over the world, it is important to be aware of the need to detect DR early and ensure regular monitoring. Early diagnosis and treatment of the retina disorder may prevent the disease from worsening and minimize the risk of vision loss [5][6]

The increasing incidence of diabetes has put a significant strain on health care systems and eye care screening programs. Several countries have been successful in introducing nationwide DR screening programmers, but there is still a lack of trained eye-care providers and access to specialized diagnostic services in many developing regions of the world [7][8][9][10]. This means that many sufferers are not diagnosed until the disease has already reached a late stage. The introduction of telemedicine and digital retinal imaging technologies has enhanced the availability of screening service, making it possible to capture and assess images remotely, and providing an opportunity for automated retinal disease screening systems [11][12].

In recent times, Artificial Intelligence (AI) has emerged as a potent technology in modern healthcare, enabling automated analysis of medical images and assisting clinicians in the diagnosis of diseases. In ophthalmology, AI systems can analyze fundus images and detect abnormalities with high ACC and speed, making a preliminary diagnosis [13][14]. Intelligent screening systems have been developed using Machine Learning (ML) techniques that have learned to identify patterns in retinal images related to disease. The use of AI and ML in retinal disease detection contributes to enhancing diagnostic efficiency and aiding in early intervention, especially in resource-limited healthcare environments [15][16][17][18].

The application of Machine Learning (ML) and Deep Learning (DL) has revolutionized the analysis of retinal images and diabetic retinopathy screening by automatically detecting disease-related features from fundus images. ML algorithms can learn discriminative patterns associated with retinal abnormalities, whereas DL models are capable of extracting complex hierarchical features directly from large-scale retinal image datasets [19]. DL techniques overcome the need for manual feature engineering and enhance the ACC and efficiency of automated screening systems in comparison

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to conventional image analysis methods. The use of AI, ML and DL has enabled the creation of intelligent retinal disease detection systems that can effectively detect DR in various stages with high ACC [20]. Such AI-driven tools can help ophthalmologists by delivering quick and precise screening outcomes, which can facilitate early detection, expand health care access, and lessen the strain on clinical screening initiatives [21][22][23].

A. Motivation and Contribution

This study is motivated by the rising incidence of diabetes and the rising risk of diabetic retinopathy, which, if left untreated, is a significant cause of avoidable blindness. It is often difficult to diagnose cases in less-developed parts of the world due to a lack of adequate screening facilities and expert ophthalmologists. More precise and dependable automated systems are still required, even if current machine learning and deep learning techniques have enhanced detection performance. Therefore, the objective of this work is to develop an effective deep learning-based approach to assist clinical decision-making and early detection for DR screening. This research offers several key contributions as listed below:

- Proposed an automated diabetic retinopathy detection framework using color fundus retinal images for early disease screening.
- Developed and evaluated deep learning models based on LSTM and GRU for accurate DR classification.
- Compared the proposed models with traditional machine learning (SVM, XGBoost) and deep learning architectures (ResNet50, DenseNet201) to validate performance improvements.
- Demonstrated the effectiveness of sequential deep learning models in capturing retinal feature dependencies for improved diabetic retinopathy detection.
- Supported early diagnosis and clinical decision-making by improving reliability and ACC in automated DR screening systems.

The justification of this study lies in the increasing need for accurate and automated diabetic retinopathy screening systems, as manual diagnosis is time-consuming, subjective, and dependent on expert availability, especially in large-scale screening scenarios. Existing approaches using traditional machine learning and standard deep learning models often fail to fully capture complex retinal feature dependencies, leading to limited performance in real-world applications. The novelty of this work is the integration of sequential deep learning architectures, specifically LSTM and GRU, for retinal image-based diabetic retinopathy classification, which is less explored compared to conventional CNN-based methods. By combining advanced preprocessing techniques with these sequential models, the proposed framework enhances feature learning and achieves superior classification ACC, thereby providing a more reliable and efficient solution for early diabetic retinopathy detection and clinical decision support.

B. Organization of the Paper

The paper is organized as follows: Section II literature reviews related work on Retinal Disease Detection, Section III details the dataset, preprocessing procedures, and model implementation, Section IV presents the experimental results along with comparative analysis, and Section V concludes the study and future research.

II. Literature Review

A comprehensive review and analysis of key research studies on retinal disease detection was carried out to guide and strengthen the development of this work. Table I summarizes recent studies in retinal disease detection, highlighting the proposed methods, datasets used, key findings, and the limitations or challenges identified in each approach.

Paul et al. (2026) provide an automated retinal disease screening framework using DL models, including CNN, VGG16, MobileNetV2, and ResNet-15 V2, to classify fundus images into Normal, Cataract, Diabetic Retinopathy, and Glaucoma categories. The efficacy of AI-based retinal illness detection systems was demonstrated by the models' evaluation on a dataset of 4,217 retinal pictures, where ResNet-15 V2 attained the greatest ACC of 90.52% and MobileNetV2 delivered competitive performance with reduced computing complexity [24].

J et al. (2025) suggested an automated method for detecting diabetic retinopathy (DR) using the ResNet-152 deep learning architecture. Using 3,662 fundus photos from the APTOS 2019 Blindness Detection dataset, the model was trained and evaluated to categories five levels of DR severity. A high classification ACC of 96.7% was shown in the experimental findings, suggesting that the suggested approach may efficiently facilitate early DR screening while lowering the time and effort needed for manual diagnosis [25].

Agarwal et al. (2025) a hybrid DL model that combines CNNs and Vision Transformers (ViTs) for diabetic retinopathy (DR) classification. The CNN component extracts local lesion features, while the ViT captures global image dependencies to improve disease severity prediction. Evaluated on the Messidor-2 dataset, the proposed model achieved an ACC of 95.26%, demonstrating its effectiveness and reliability for early DR screening and diagnosis.[26].

Rastogi et al. (2024) Automated retinal disease classification system using convolutional neural networks (CNNs) and transfer learning techniques. The study evaluated several pretrained models, including VGG19, ResNet50, EfficientNetB0, MobileNetV2, InceptionV3, and DenseNet121, for classifying retinal images into Normal, Glaucoma, Diabetic Retinopathy, and Cataract categories. Experimental results showed that EfficientNetB0 achieved the highest classification ACC of 90.95%, demonstrating its effectiveness for automated retinal disease screening [27].

Aurangzeb et al. (2023) focused on the challenges of retinal vessel segmentation from fundus images and proposed a modified Colons GNet model with data augmentation and intelligent contrast enhancement techniques. The model effectively addressed challenges such as central vessel reflex, bifurcation, crossover, thin vessels, and lesion presence. Experimental results on the DRIVE, CHASE_DB, and STARE datasets achieved accuracies of 0.966, 0.971, and 0.972, respectively, demonstrating the effectiveness of the proposed approach for automated retinal image analysis and early eye disease detection [28].

Johnson et al. (2022) an automated diabetic retinopathy (DR) diagnosis system using a concatenated deep learning model based on DenseNet121 and Inception-ResNetV2. The extracted features from both models were integrated using a multilayer perceptron (MLP) classifier to categorize fundus

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images into No DR, Non-Proliferative DR, and Proliferative DR. Experimental results demonstrated improved performance compared to single models, achieving 91% ACC and an F1-score of 90%, highlighting the effectiveness of the proposed approach for automated DR screening [29].

TABLE I. RECENT STUDIES ON RETINAL DISEASE DETECTION USING MACHINE LEARNING TECHNQIUES

Author	Proposed Work	Dataset	Findings	Limitations & Future Work
Paul et al. (2026)	Developed an automated ocular disease screening framework using CNN, VGG16, MobileNetV2, and ResNet-15 V2 for detecting Normal, Cataract, DR, and Glaucoma from retinal fundus images.	4,217 retinal fundus images (4 classes)	ResNet-15 V2 achieved 90.52% accuracy, while MobileNetV2 provided efficient performance with lower computational cost.	Limited to four ocular diseases and a single dataset. Future work may focus on larger multi-center datasets, explainable AI, and real-time clinical deployment.
J et al. (2025)	Proposed an automated DR detection system based on ResNet-152 for classifying five stages of diabetic retinopathy.	APTOS 2019 Blindness Detection Dataset (3,662 fundus images)	Achieved 96.7% accuracy in DR detection and classification.	Performance should be validated on diverse datasets and real-world clinical environments. Future work can explore lightweight architectures and explainability.
Agarwal et al. (2025)	Introduced a hybrid CNN-Vision Transformer (ViT) model combining local lesion extraction and global feature learning for DR classification.	Messidor-2 Dataset	Achieved 95.26% accuracy for DR severity classification.	Computational complexity of hybrid models remains high. Future work may focus on model optimization and deployment in low-resource healthcare settings.
Rastogi et al. (2024)	Evaluated transfer learning models including VGG19, ResNet50, EfficientNetB0, MobileNetV2, InceptionV3, and DenseNet121 for retinal disease classification.	Labeled retinal fundus image dataset (Normal, Glaucoma, DR, Cataract)	EfficientNetB0 achieved the highest 90.95% accuracy.	Generalization on larger datasets was not investigated. Future work should focus on multi-disease detection and clinical validation.
Aurangzeb et al. (2023)	Proposed a modified ColonSegNet model with contrast enhancement and data augmentation for retinal vessel segmentation.	DRIVE, CHASE_DB, and STARE datasets	Achieved accuracies of 96.6%, 97.1%, and 97.2%, respectively.	Focused only on vessel segmentation rather than disease classification. Future work may integrate segmentation with automated disease diagnosis systems.
Johnson et al. (2022)	Proposed a concatenated deep learning model combining DenseNet121 and Inception-ResNetV2 with MLP for DR classification.	Fundus image dataset with three DR categories	Achieved 91% accuracy, precision, recall, and F1-score.	Performance needs validation on larger and more diverse datasets. Future work can incorporate explainable AI and severity grading.

Research Gaps: There are still a number of research gaps in diabetic retinopathy identification, despite notable progress made with machine learning and deep learning approaches. Most of the current techniques are based on CNN-type architectures that might be unable to capture long-range dependence and long sequential information in retinal images. Furthermore, most of the methods are specific and have a restricted generalization ability because of dataset imbalance, the diversity of images and insufficient image pre-processing methods. Therefore, there is still a need for more robust and efficient models that can improve feature representation, enhance classification ACC, and ensure reliable performance in real-world clinical screening scenarios.

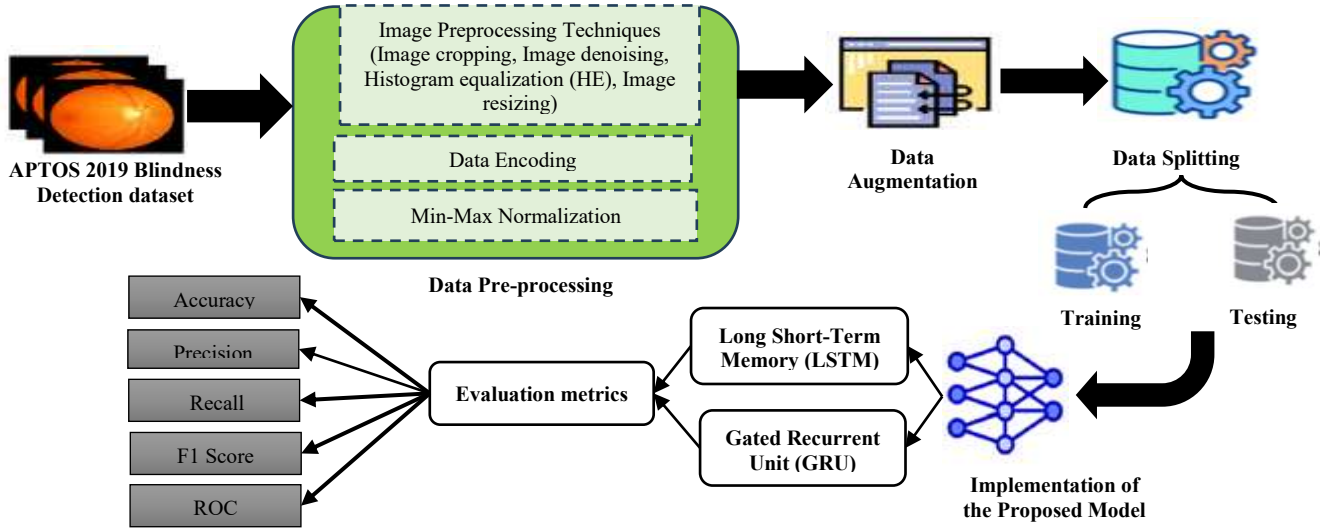


Fig. 1. Proposed Flowchart for Retinal Disease Detection using Machine Learning

III. RESEARCH METHODOLOGY

The suggested approach uses the APTOS 2019 Blindness Detection Dataset, which is made up of retinal fundus images that have been pre-processed using image cropping, denoising, histogram equalization, resizing, augmentation, and normalization to enhance image quality and model readiness. The dataset is then divided into a training set of 70% and a test set of 30% after label encoding. The LSTM and GRU DL models are used to learn sequential feature representations for DR classification. Modelling performance is evaluated using the confusion matrix and a variety of

J. Glob. Res. Elec. Comm., 2 (10):08-15
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classifiers, including ACC, PRE, REC, F1, and ROC analysis. The suggested pathway for the detection of retinal diseases is displayed in Figure 1.

The subsequent section provides a detailed description of each of the proposed methodology stages:

A. Data Gathering and Analysis

The APTOS 2019 Blindness Detection Dataset was used for this study, with a total of 3,662 retinal fundus images labeled for use. Each image was classified into one of the following categories: DR class (1) and No_DR class (0), with 1857 images categorized as DR and 1805 as No_DR. Class-wise distribution of the given data was studied and presented graphically using bar plots as shown below:



Fig. 2. Distribution of DR and No_DR Images in the Training and Test Subsets of the APTOS 2019 Dataset

Figure 2 shows the distribution of DR and No_DR images in the training and test sets. The bar chart displays the data, where there is a close balance between the two classes and a similar number of images in each category. This even distribution helps to reduce classification bias and enables precise model training and testing.

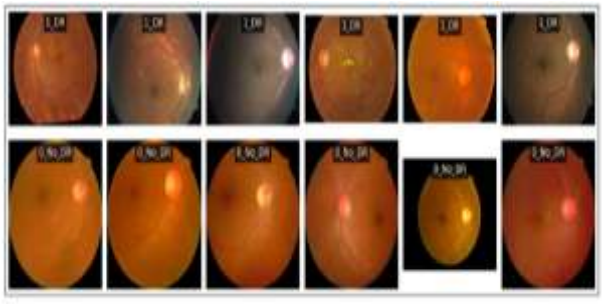


Fig. 3. Representative Fundus Images from the APTOS 2019 Study for the Two Classes: Diabetic Retinopathy (DR) and No-Diabetic (No_DR)

Figure 3 displays the typical fundus images from two classes, Diabetic Retinopathy (DR) and No Diabetic Retinopathy (No_DR). DR class images show signs of disease (including microaneurysms, hemorrhages and abnormal vascular patterns). The No_DR class images appear relatively normal with features that look fine in the retina, but with no apparent pathological features.

B. Data Pre-Processing

The APTOS 2019 Blindness Detection dataset was used for data preparation. The preprocessing pipeline involved cropping the images, denoising, histogram equalization (HE), resizing, data augmentation, label encoding, and normalization. These steps were taken to increase the quality of the images, to increase the features, and to make the data usable for good model training. The major preprocessing methods are summarized below::

- **Image cropping:** The unnecessary black background around the fundus images was removed by image cropping. The preprocessing stage lowers irrelevant information and increases the ACC of the analysis by keeping just the retinal area that contains significant features including blood vessels, the optic disc, and the macula.
- **Image denoising:** Images can lose some of their clarity and interpretability when noise gets in the way of denoising. Enhance the image's visual quality by eliminating noise. To remove noise from dataset, Gaussian blur is applied using cv2.GaussianBlur().
- **Histogram equalization (HE):** The pictures are subjected to Histogram Equalization (HE). By shifting the brightness of pixels, histogram equalization improves an image's contrast.
- **Image resizing:** The dimensions of each image are adjusted such that they are all 200 × 200 × 3 pixels in size. In this case, the size of the pixels are indicated by the first two numbers, while the existence of the RGB (red, green, and blue) color channels is shown by the third number.

C. Data Augmentation

Augmentation is an essential step in the training phase. Image class distribution is balanced before they are input into the models. This is accomplished by using the augmentation approach. In this method, additional pictures are added to each class by means of displacement, zooming, and rotation (the former of which mimics various viewing perspectives).

D. Data Encoding

The labels for the categorical classes were transformed into numerical values so that the deep learning model could handle them using Label Encoding. This transformation helps in efficient learning and accurate classification during training process.

E. Min-Max Normalization

The data were normalized using the Min–Max normalization technique to scale all values between 0 and 1. This pre-processing technique enhances the performance of the model by maintaining the same range of features and by minimizing the effect of extreme values. The normalization process can be mathematically expressed as follows Equation (1):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where X represents the original value of the feature, X' is the normalized value, X_{min} is the minimum value of the feature, and X_{max} is the maximum value of the same.

F. Data Splitting

The data is divided into training and testing sets in a ratio of 70:30, where 70% is used for training and 30% for testing, before model training. The training set is used for learning the underlying patterns of the data, while the testing set is used to test the performance and generalization ability of the trained model.

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G. Implementation of the Proposed Model

In this study, LSTM and GRU models were implemented for retinal disease detection in diabetic retinopathy screening.

1) Proposed Long Short-Term Memory (LSTM) Model

Long Short-Term Memory (LSTM) is a powerful recurrent neural network architecture designed to model sequential data and capture long-term dependencies. Unlike traditional RNNs, LSTM overcomes the vanishing gradient problem through the use of memory cells and gating mechanisms. These gates regulate the flow of information, allowing the network to retain important features and discard irrelevant data. As a result, LSTM can effectively learn complex patterns from retinal images and improve classification performance. The LSTM model is used in this study to accurately detect DR and assist in automated retinal disease screening.

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{2}$$

where f_t is the function that stores the previous cell state's information. The role of this gate is to regulate the memory updates and to enhance the model's ability to capture the relevant retinal features. The forget gate is given in Equation (2).

$$C_t = f_t \odot C_{t-1} + i_t \odot \bar{C}_t \tag{3}$$

Where the old state of the cell and new information are fused to produce the new state of the cell. In this way, LSTM can maintain significant feature representations and improve classification performance, as shown in Equation (3).

The LSTM is optimally designed with a learning rate of 0.001, a batch size of 32, 100 hidden units, a dropout rate of 0.5, trained for 30 epochs with the Adam optimizer and binary cross-entropy loss function for best performance in the classification of diabetic retinopathy.

2) Proposed Gated Recurrent Unit (GRU) Model

Gated Recurrent Unit (GRU) is an effective variant of the recurrent neural network (RNN) designed to overcome the limitation of capturing sequential dependence in RNNs with low computational overhead. Compared to LSTM, GRU has fewer trainable parameters and only the reset and update gates. The design allows quicker training and reduced memory usage while maintaining comparable performance. The gating mechanisms control the flow of information through GRU, allowing it to learn relevant feature representations effectively. This study employed GRU model for screening DR with the aim of achieving accurate and reliable classification for retinal diseases.

$$z_t = \sigma(W_z[h_{t-1}, x_t] + b_z) \tag{4}$$

The amount of information from the previous hidden state to be retained is determined by z_t. This mechanism is useful to retain essential features and to enhance the learning efficiency in the classification process, where the update gate is defined in Equation (4).

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \bar{h}_t \tag{5}$$

The hidden state update operation of the GRU model. This is a mixture of the information it stored in the last hidden state and the new features it has learned to create the current hidden state. This process allows the model to adequately learn patterns and promote the ACC of the detection of DR in Equation (5).

The GRU model was trained for 30 epochs using the Adam optimizer and a binary cross-entropy loss function, which was set to 128 hidden units, 0.4 dropout rate, and a batch size of 32, to ensure efficient feature learning and stable convergence.

H. Evaluation Metrics

The performance of the proposed design was evaluated using multiple metrics. A confusion matrix was created to summarize classification results, showing the number of true and false predictions for each class. Key values like True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) were derived from this matrix. These values were then used to calculate some performance measures that are crucial such as ACC, PRE, REC and F1, which were defined in Equation (6) to (9):

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+Fp+TN+FN}} \tag{6}$$

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \tag{7}$$

$$Recall = \frac{\text{TP}}{TP+FN} \tag{8}$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{9}$$

ACC represents the proportion of correct predictions among all the predictions made by the trained model. PRE is the proportion of positive instances successfully predicted to all positive instances predicted by the model. REC number of events that were correctly predicted as positive/number of events that should have been predicted as positive. F1 score is a combination of the harmonic mean of PRE and REC, that is, it helps to balance REC and PRE. The ROC curve graphically shows the relationship between the fraction of positive instances that are correctly identified and the fraction of negative instances that are incorrectly identified, for various decision thresholds.

IV. RESULTS AND DISCUSSION

The Python programming language is used on Kaggle Notebooks to carry out the model. The internal storage is up to 73GB, there is 29GB of RAM and the 15GB GPU has a copy of the graphics card. It is capable of supporting heavy deep learning models. In this work, used a number of libraries, such as TensorFlow, OpenCV, Pandas, and Matplotlib, to develop framework.

A. Results and Performance Analysis

The experimental setup is presented in this section and the performance of the presented models in the DR screening is evaluated. The results showed that the proposed method is efficient and reliable in detecting retinal abnormalities. To compare the classification capabilities of both the LSTM and GRU models, ACC, PRE, REC, and f1 are taken into consideration and are compared in Table II. The performance of both models was excellent, showing their high capability in detecting DR. The LSTM model achieved an ACC of 98.64%, PRE of 98.14%, REC of 99.19%, and F1 of 98.66%, while the GRU model obtained an ACC of 98.36%, PRE of 97.62%, REC of 99.19%, and F1 of 98.40%. The strong REC rates obtained from both models demonstrate the models' ability to accurately capture the cases of DR. In conclusion, the LSTM model outperformed the other models in most of the evaluation metrics, indicating its effectiveness and robustness for automated retinal disease screening.

J. Glob. Res. Elec. Comm., 2 (10):08-15
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TABLE II. CLASSIFICTION RESULTS OF PROPOSED MODELS RETINAL DISEASE DETECTION

Matrix	Long Short-Term Memory (LSTM)	Gated Recurrent Unit (GRU)
Accuracy	98.64	98.36
Precision	98.14	97.62
Recall	99.19	99.19
F1-score	98.66	98.40

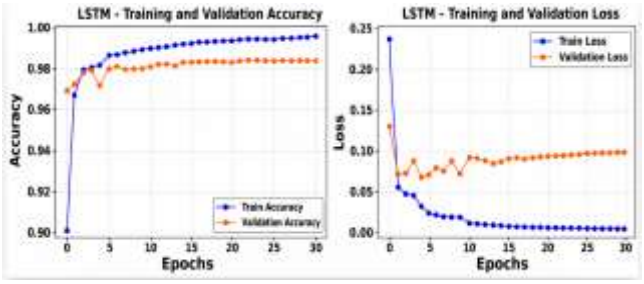


Fig. 4. Accuracy and Loss Curve for LSTM Model

The training and validation performance of the LSTM model is shown in Figure 4 over 30 epochs. The ACC of the training and validation sets rises quickly and tends to 100%, and the validation set has the ACC of 98-99%, which indicates good classification ACC and generalization. Likewise, the training loss drops sharply but the validation loss varies only slightly in the first few epochs. The similarity in training and validation metrics indicates that the LSTM model is learning effectively, and there is not much overfitting being observed, which means it performs well on the dataset.

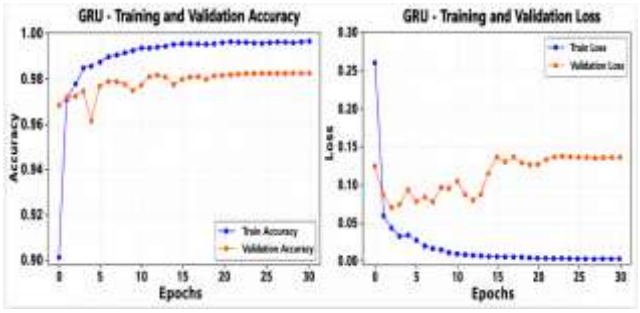


Fig. 5. Accuracy and Loss Curve for GRU Model

The training and validation performance of the GRU model for 30 epochs is displayed in Figure 5. The training ACC is quickly reaching 100% and the validation ACC is reaching 98%, which shows that the training is good and the generalization is good. Likewise, there is a high drop in training loss, virtually to zero, and a relatively stable validation loss with slight variations. The training curve is very close to the validation curve, indicating low overfitting and good predictive power.

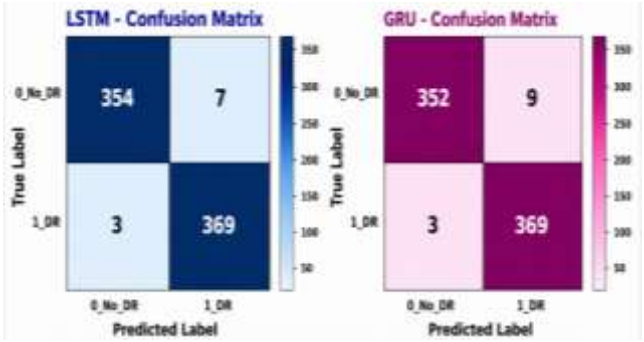


Fig. 6. Confusion Matrices for the Proposed Models

The confusion matrices of the proposed LSTM and GRU models for diabetic retinopathy classification are shown in Figure 6. Both models work well, with many of the entries on the main diagonal being correct and a few off-diagonal entries being incorrect. The results show high sensitivity and specificity in the classification of DR and No_DR classes, and the LSTM model shows slightly better overall classification performance than the GRU model.

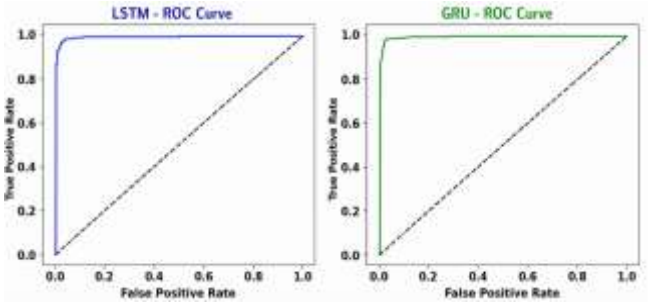


Fig. 7. ROC Curve for the Proposed Models

The ROC curve for the proposed LSTM model and GRU model for diabetic retinopathy classification is shown in Figure 7. Both curves are close to the upper left corner and above the reference diagonal, good discrimination ability, high sensitivity, high specificity. The results validate the effectiveness of the proposed models for automated DR detection.

B. *Comparative Analysis*

The performance comparison of the proposed models with existing machine learning and deep learning models is presented in Table III. The comparison includes SVM, ResNet50, DenseNet201, and XGBoost models, which achieved accuracies ranging from 82% to 92.99%. XGBoost showed the best performance with an ACC of 92.99%, a PRE of 92.72%, a REC of 92.52 percent and an F1 score of 92.32%, among the existing methods. The proposed recurrent neural network-based models, however, performed much better than all other benchmark models. The proposed LSTM model attained a maximum ACC of 98.64%, along with a PRE of 98.14%, a REC rate of 99.19% and an F1 of 98.66%, while the proposed GRU model obtained an ACC of 98.36%, a PRE of 97.62%, the REC rate of 99.19% and an F1 of 98.40%. The results underscore the superior performance of the models proposed for accurate detection of DR, where the LSTM model performed best in all the evaluation measures.

TABLE III. COMPARISON OF DIFFERENT MACHINE LEARNING AND DEEP LEARNING MODELS FOR RETINAL DISEASE DETECTION FOR DIABETIC RETINOPATHY SCREENING

Model	Accuracy	Precision	Recall	F1-score
SVM[13]	82	-	82.50	-
ResNet50[30]	84.1	-	-	77.1
DenseNet201[31]	89.17	95.81	81.80	98.73
XGBoost[11]	92.99	92.72	92.52	92.32
Proposed LSTM	98.64	98.14	99.19	98.66
Proposed GRU	98.36	97.62	99.19	98.40

C. *Results Discussion*

The proposed LSTM and GRU models provide remarkable classification performance and demonstrate the ability to effectively learn complex patterns from retinal images, making them highly suitable for diabetic retinopathy screening. Both models exhibited an ACC of over 98%, significantly better than current machine learning and deep

learning methods. The high REC rate (99.19%) shows they have a good ability to accurately detect cases of DR, reducing the chances of missed diagnoses. Besides, the high ACC and F1-scores ensure that the predictions are both accurate and reliable, minimizing false predictions. LSTM achieved 98.64% ACC, which indicates the superior effectiveness, robustness and suitability of the model in accurate and automated retinal disease detection for clinical screening applications, among the two models.

V. Conclusion and Future Study

Diabetic retinopathy (DR) is a progressive complication of diabetes that if left undetected, can cause vision loss or blindness. It is marked by abnormalities of the retina including microaneurysms, exudates, and hemorrhages, which are important markers of diagnosis. Early screening of retinal fundus images plays a crucial role in timely detection and treatment, thereby preventing severe visual impairment in diabetic patients. With the advent of computer-aided diagnosis and data-driven machine learning methods, there is a great potential for an effective DR diagnosis. The comparative analysis of the classifiers shows that traditional classifiers like SVM and XGBoost perform reasonably well for DR detection, and deep learning models like ResNet50 and DenseNet201 achieve better ACC. The proposed LSTM and GRU models, however, outperform all the other methods with highest ACC of 98.64% and 98.36%, respectively. The results revealed that sequential deep learning models are more effective in extracting discriminative retinal features, that is, more effective in improving and reliable screening performance for DR. Further research will involve larger multi-center datasets, multi-class classification of DR severity, and better deep learning architectures for enhanced robustness and clinical utility.

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