MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 2260-2267

A Deep Learning–Based Approach for Detecting Normal and Abnormal Diabetic Retinopathy

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Abstract:
Diabetes can gradually sneak up on you to impair your eyesight. When retina measurements are not taken often, small but significant changes in retina are missed out. If detected early enough, permanent vision loss can be stopped. Nevertheless, a great deal of time is wasted reviewing the retinal scans manually. Different reviewers may arrive at different conclusion about a decision. Currently, trained specialists examine the images and do this type of work. The Current Approach Seems Unfeasible For At Scale Implementation Of The Solution. It is a deep-learning-based system that makes an effort to distinguish between normal and abnormal status of retina without any kind of human involvement. To design a system to capture images spatially, morphologically and temporally, novel deep networks architectures have been proposed. The architectures utilize CNN, RNN, bi-directional RNN, auto encoders and VGG-16 network. Other learning techniques such as Decision Forest are used to compare performance assessment Publicly available Diabetic Retinopathy datasets yield experimental results. The suggested method attains excellent accuracy with solid generalization across various. Such images are good quality and effective for early DR detection. An automatic system. Ophthalmologists may perform screenings quickly and routinely to lessen heavy work. This. The structure enhances strength and feature representation and ability to separate normal. using an amalgamation of models to create an abnormal retinal image.

Keywords: Diabetic Retinopathy, Deep Learning, Medical Image Analysis, Retinal Fundus Images, Automated Diagnosis, Explainable Artificial Intelligence, Dataset Diversity, Human–AI Collaboration.

INTRODUCTION

People with diabetes who use their visual system regularly get diagnosed with vision loss due to diabetes too late. While checkups can help slow down the damage, not everyone has access to seeing a specialist. The small changes that take place in the lining of the eye first – swelling pocket, bleeding, leaking of fluid. What the first physician may deem a condition the second physician may not. drained
When looking at images for extended periods of time, such as hours, we will have blurry judgment. The little signs slip past our notice when the mind wanders.

It is not speed, nor intelligence, that makes the difference. It is how deep learning pays attention. It's noticing works differently. The doctor isn't trained to notice symptoms that take place in a patient's body. Although it might have, it has no memory of that. Can we examine previous patient files? It doesn't even bother taking notes for a second. It detects patterns across grids of tiny dots and draws connections without naming the thing the dot is. Human tags do not add anything to its inbuilt conclusions. The value is found right there.

It operates via convolutional neural networks. A grid type system helps in processing grid shaped data like images. A neural network application functions based on examples rather than a set of fixed rules. A collection of eye scans are labeled by the professionals in the health care category. This set forms the ground, which contains various labelled pictures. One image from the set goes through different levels. One neural level responds to the vision of simple lines; the other responds to patches of color.

It is true that it does not really matter whether the classification of disease localizes lesions or not. Several top-performing models forgo the localization of microaneurysms as they base their decision on textures globally. For instance, the way in which asymmetrically blood vessels branch, there is a patchy brightening across the retina, colour differences at the junction of the veins etc. For a human doctor, these are all easy to brush aside, figuring they're just random clutter. The algorithm's signal is determined by how it looks.

When you train properly, you walk a line. On rare occasions, if you do take any shortcuts, we treat the outcome as ordinary business. If it receives too many altered images like rotated, mirrored, colours changed so it soon begins to pick up errors generated by the software rather than disease symptoms. Choosing a data is as important as logic coding. While collections like EyePACS and Messidor were valuable, some issues remain. Images usually come from busy hospitals in cities where money flows easily. When applied in other realms, things like illumination levels and machine variety become a consideration, as do motifs, not merely contraptions.

Not anything can be ruled out, although the checks may appear to be robust. Testing which uses an independent source for data is called external check, as opposed to one involved in development. Most of the time it works in the practice when the one uses different data instead of the theory. AUC is an example of a metric we use to assess performance in distinguishing ill from disease-free outcomes. While a good score does demonstrate the absence of issues but certainly not all the issues because there are some issues at the end of the range which miss out always. In reality we can use most of the checks dedicatedly for spotting.

Unexpected adjustments to the picture affect the final result. Seems like not much has been said about it, though this happens rather early on. Playing light does not cover the raw scan of the eyes uniformly. A completely random choice. The focus is not always tight. The area that is covered may not be exactly the same. To address this, certain deep learning systems remove the edges or flatten the brightness. As a result, extremely subtle damage in the far periphery can be completely wiped out. The retina's outer region occasionally has frayed edges, which indicates a serious and progressive deprivation of blood supply to the eye. Unexpected cues are easily missed by observers viewing from the outside.Figures wobble when life doesn't fit into neat boxes. Guesses come dressed as certainty, yet they shift with hidden nudges - like the lens that caught the image or who showed up most in past data. Labels spill beyond clear edges because machines speak in shades, never absolutes. What looks solid often cracks under closer glance.

A fresh look at diabetic eye care shows deep learning fits better beside doctors than in their place - like a well-timed nudge when decisions grow tough. Instead of taking over, it adjusts the view exactly when needed.

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LITERATURE SURVEY

A slow damage to tiny blood vessels in the eye often follows long-term diabetes, making it a top reason people lose sight across the world. Spotting changes early plus getting care fast can stop total vision loss. Most clinics still check eye photos by hand, done each time through careful look from eye doctors - an effort that takes much time, costs a lot, yet varies between experts. Because of these hurdles, scientists dove into building smart tools that find signs without help, where teaching computers how to learn alone has turned out strongest lately.

At first, research showed deep convolutional neural networks were able to pick up key signs in retina photos by themselves, using just regular eye scans. Because of findings like those in study [1], followed by results from team [2], scientists saw these models match skilled doctors in spotting issues reliably across big groups. With such proof came a shift - many began building tools around CNNs for catching diabetic retinopathy early. Instead of relying on hand-labelled damage markers, machines learned patterns naturally, opening paths toward automated evaluation at scale.

Later work turned to transfer learning because labelled medical images are hard to get. Scientists did not begin from nothing however did choose systems that were already trained like VGG, ResNet, DenseNet and Inception. A pre-trained system helped achieve better results faster. Furthermore, it has been observed that these systems first learn small features like edges and ripples, then larger shapes and objects. Consequently, they take away with them anything from small texture-like information to complex disease signatures in retina scans. Because of this hierarchical understanding, the approach is highly suitable for anomaly detection in medical images. Although these networks were not trained on medical images, their adaptability feature makes them a potent solution in this scenario.

Researchers can combine different types of learning instead of adopting just one kind of model, so that results can improve in varying situation. Papers [5] and the Springer publication cited [6] connected the outputs of convolutional networks with custom texture features to achieve sharper classification and reduced errors. As discussed in [19], the integration of classical texture features with recent neural features showed to be beneficial while working with faint lesions where errors tend to happen more. Hybrid systems like these suggest that even earlier techniques may still have much to offer when coupled with later ones. The analysis of the severity of the diabetic retinopathy in eyes has become more important compared to just its detection. In papers [7], [8] and [11] researchers propose both a multi-class system which divides cases into several groups, e.g. normal, mild, moderate, severe or proliferative. A decent result is observed in these approaches for their respective classes. Nevertheless, some findings indicate that these approaches struggle to indicate early signs since these signs are too similar to each other. Due to the infrequent occurrence of certain levels in available datasets, the models find them harder to learn. Numerous surveys as in [9], [15] refer to this ongoing problem as one of the largest obstacles remaining for screening tools today. Recently there is more research activity being concentrated on developing models that are easier to interpret. Many physicians having the hesitation over whether to trust deep learning as it is right most of the time. Research articles [9] and [16] worked on a solution to make the AI's decisions more interpretable.

Although attention maps appear in some areas and gradient-based visuals in others, both simply highlight sections of the data that the system relies on. The human still makes the diagnosis, the difference being that we have snapshots that match the machine thought. The presence of such evidence enhances trust as the doctor understands which characteristic influenced the outcome. These days the system performance and preferably testing outside laboratories is becoming more pronounced particularly in constrained resources of tools and power environments. Most deep learning models that have a heavy computational requirement, need a powerful machine for their training and inferencing. These make them difficult to use in a rural environment or on embedded portable devices. As a result, lightweight versions for deployment on small devices have started making appearances. This implies that less robust CNN architecture can effectively estimate the ailment at a low-energy consumption rate. Research into advanced enhanced network designs has increased the accuracy of the obtained results. The latest articles published by Springer- like in [10], [13], [15], explore the role of attention, integration improvement at different scales of features or optimized learning rules. Consequently, these systems are able to pinpoint small bulges, bleeding points, or fluid leaks in patients and provide a more accurate analysis of health condition. The result is enhanced in assessing the severity of the disease. The concepts put forth in Chapters [12] and [14] encompass a series of steps, combining the cleaned data with layered grouping to improve the judgment of seriousness.

A review of several surveys and review papers presents a broad picture of present achievements. According to papers like [9], [15], and [16], datasets, data preparation, metrics plus challenges in real-world applications have been discussed. The same pattern keeps occurring repeatedly – a lack of common benchmark testing, a lack of testing on divergent data sources and a weak link to end-to-end clinical workflows. In addition, validation of image quality and guiding next steps in treatment often appears necessary when developing automated tools for diabetic retinopathy. As shown in ResearchGate papers [21]–[24], several CNN configurations and hybrid deep learning techniques leveraging several datasets have been explored in published research. Deep learning methods show promising performance in diabetic retinopathy detection and classification, as seen in strong reported results. Yet, many depend on relatively small-scale data and laboratory-type conditions – so extensive-testing in real-life clinical settings certainly seems essential. Although there have been advances, there remain gaps between theory and practice.

On the whole, many studies have shown how deep learning has improved the detection of diabetic retinopathy by machine. Techniques based on CNNs as well as hybrid approaches have higher performance than traditional ones. Nevertheless, they currently face challenges that hamper clinical application. This makes detecting early signs in individuals of diverse ethnic backgrounds very difficult. Issues also arise when mechanizing interpretability or optimizing computation. Further work is required to integrate these algorithms in real-world screening settings. Without tackling such barriers, widespread trust and practical adoption might stay out of reach.

METHODOLOGY

The proposed work adopts a systematic workflow to automatically detect normal and abnormal Diabetic Retinopathy using Deep Learning. As shown in figure 1, the complete development of the proposed methodology will take place in a sequential manner. Furthermore, the working of the proposed technique begins with retinal image dataset preparation. Following segmentation, the images undergo pre-processing steps that ensure that the images are in similar format. Later, they are used to extract out the required features. Upon extraction, the pre-processed images are used to train the network using these features. The model can now begin giving predictions for images that are not part of the dataset. Only then does the evaluation of the model take place by metrics.

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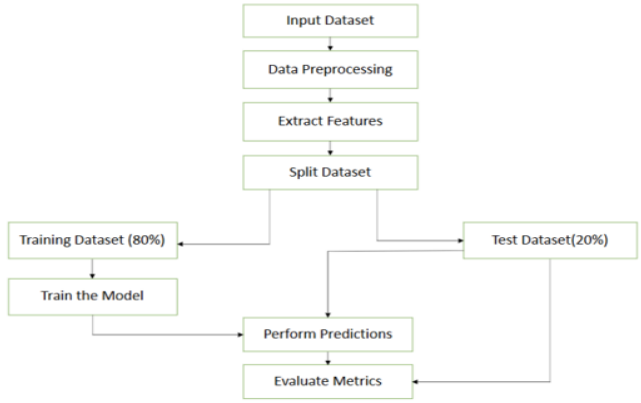
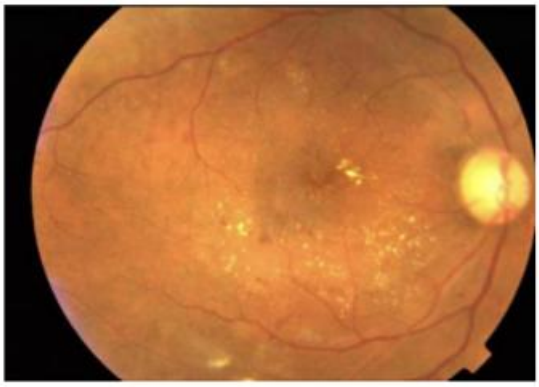


Fig 1 Flow Chart for Project

A. Gathering Data from User:

In the first stage, the user interacts with application. The user chooses the type of deep learning model for which damage value prediction from the image is required. The user must next upload a retinal fundus image of the eye for which the damage value has to be predicted by the system. The subsequent step of the system checks whether the image is a valid one and is in the correct format. At this stage, the application is made more interactive and flexible as users can test.

Sample Images:



B. Data Preparation and Preprocessing:

As soon as the image is received, it will be prepared for assessment. The image was resized to a fixed size so that all the models can process it properly. Normalization of brightness and contrast is done and an effort is made to filter out noise. This process enhances the quality of the images and ensures that the important retinal features are highly visible and can be well learnt from the images.

C. Model Selection and Initialization:

The model chosen by the user is loaded by your system. This system can employ a range of deep learning models including CNN, RNN, LSTM, and more. The prediction preparation of each model is done by your system. Thus the methodology would serve as a single platform for testing all types of deep learning approach.

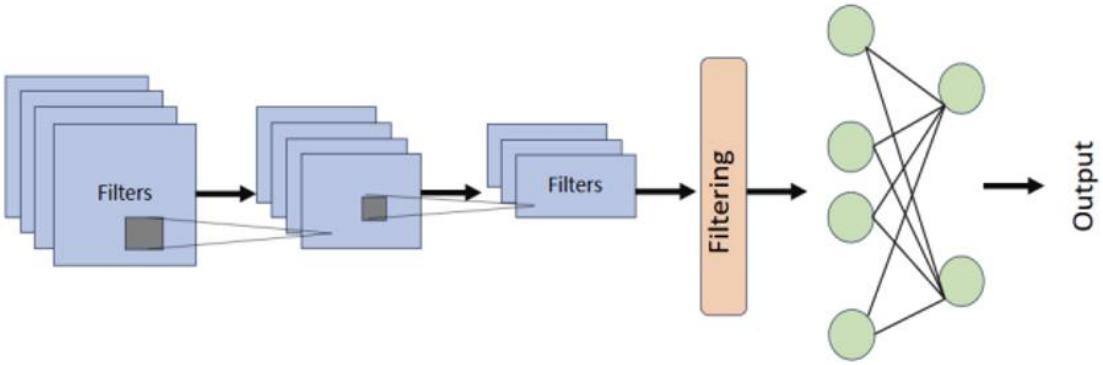


Fig 2: Architecture of CNN

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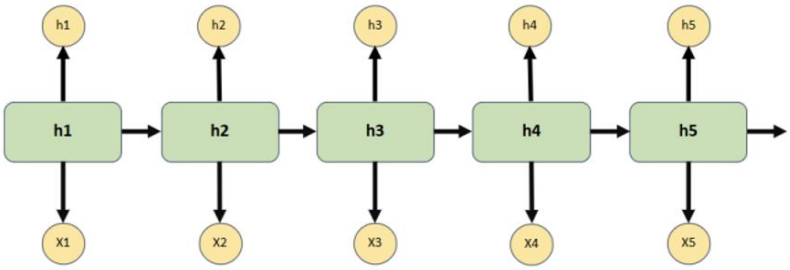

Fig 3: Architecture of RNN

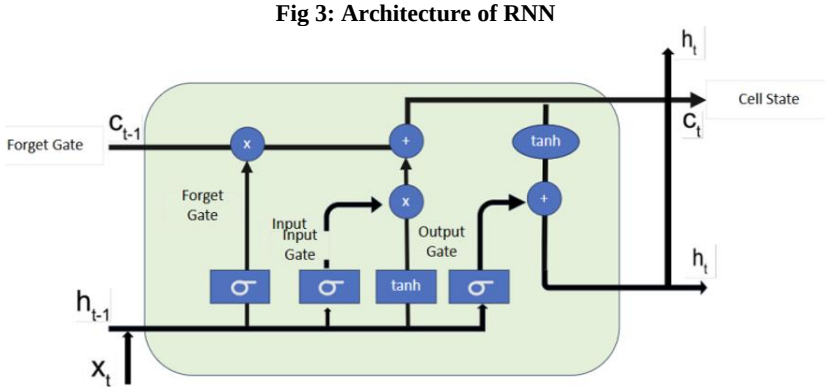

Fig 4: Architecture of LSTM

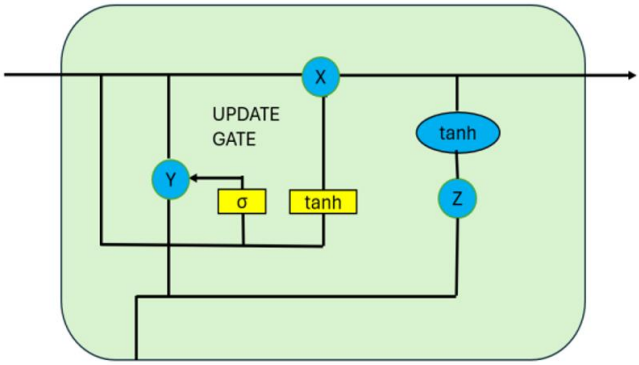

Fig 5: Architecture of GRU

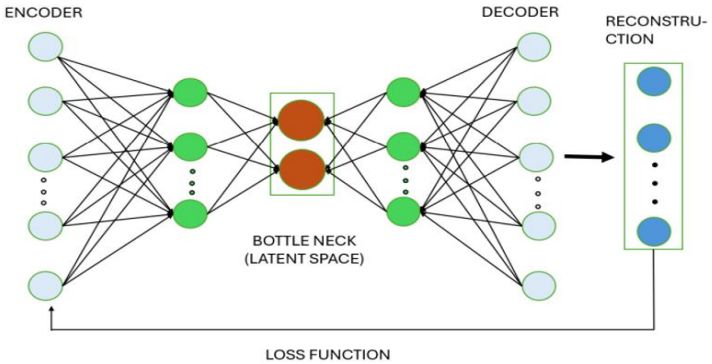

Fig 6: Architecture of Autoencoders

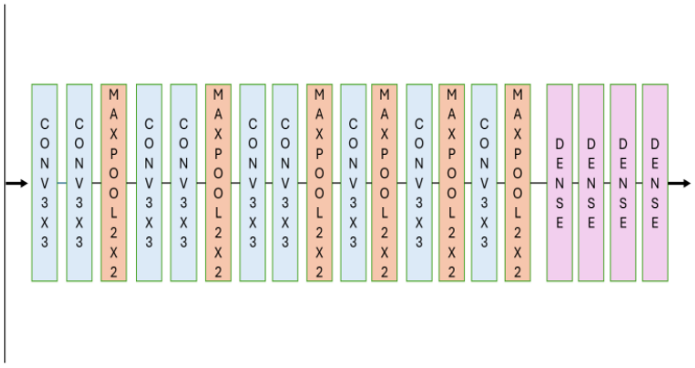

Fig 7: Architecture of VGG-16

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D. Feature Extraction and Learning:

Extracting Features and Learning. Our selected model starts picking up useful and relevant patterns from the retinal image. The step stylistically extracts useful visual information in the form of texture, edge, abnormal structure, object, etc. These features are produced by the convolution layers in CNN and VGG model. The models of RNN, LSTM, and GRU learn these features in a sequential manner. The Autoencoder learns hidden representations that can distinguish between normal and abnormal images. With this step, a manual-feature designing gets eliminated.

E. Prediction and Classification:

The model predicts normal or abnormal input images after the stage of feature learning. The output is a probability score, which is further converted into a final decision. As a result, in the categorization stage the system can diagnose DR automatically without the human intervention.

F. Result Display and User Interaction:

The app interface displays the result to the user. It shows the model chosen by the user, output (normal or abnormal) and confidence level associated with the prediction. In this manner, the user is aware of the output. To illustrate, the user can compare how various models interpret the same image.

G. Data Storage and Logging:

Finally, the system stores the input image details, selected model, and prediction result in the database. This data can be used later for performance evaluation, model improvement, and research analysis. Storing this information also helps in building future datasets and improving system accuracy.

RESULTS:

Results generated by our model are given in this part. Various models like CNN, CNN-LSTM (RNN-backed), and Auto encoder models have showcased how a deep learning-based retinal disease detection framework can be created. The results consist of the images of the developed application and the confusion matrix and class-wise performance of the system.

4.1 Dataset Split and Experimental Setup:

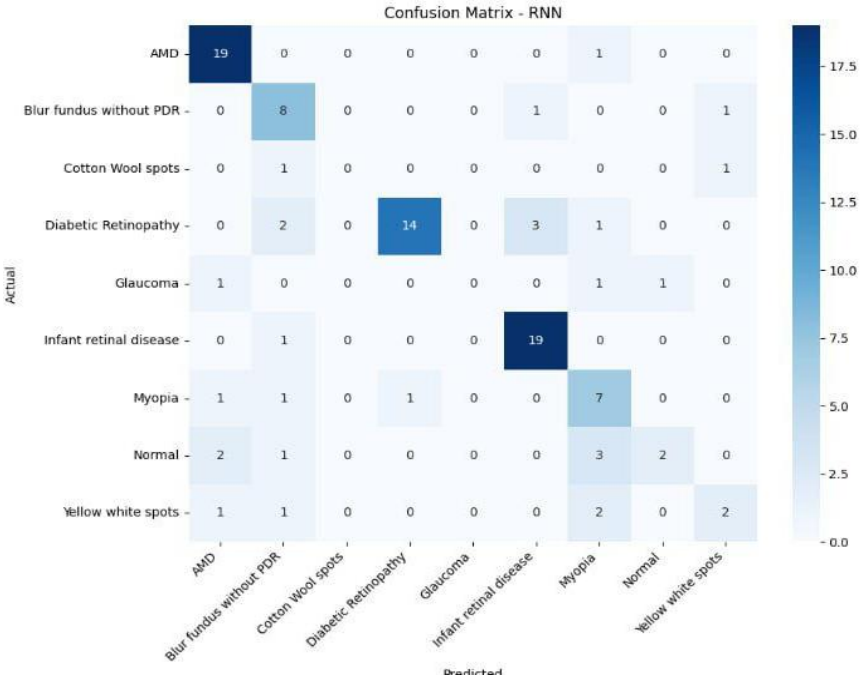
The dataset is divided into a training and testing set in an 80:20 ratio. The feature representation of image can be learnt and model parameters optimizations from training dataset. We test the dataset to evaluate the accuracy of our model without any bias. The eleven disease classes that have been considered are AMD, VDP, cotton wool spot, diabetic retinopathy, glaucoma, infant retinal disease, myopia, normal, yellow-white spot. Confusion matrices were utilized to measure the performance which is a reliable performance measure for classification tasks. Together with the.

4.2 Model-wise Performance Analysis:

Deep learning models have been tried out over the years to check their learning ability and classification power. For example, the CNN model produces effective classification results for the major retinal disorders. The deep features learned at above-mentioned diseases are more pronounced which longitude static. In addition, the CNN misclassifies the classes with similar appearances

4.3 Confusion Matrix Analysis:

The confusion matrix for RNN model as shown in Figure shows that many classes have a strong showed diagonal dominance. It indicates that the RNN model has accurately classified AMD, infant retinal disorder, diabetic retinopathy, and other diseases. There is minor confusion



between the similar retinal. The confusion matrix of CNN indicates more misclassifications, particularly between diabetic retinopathy and glaucoma-related patterns, suggesting that spatial features are not effective for the classification of complex retinal diseases. The hybrid and sequential learning models are better at distinguishing overlapping retinal characters compared to the standalone CNN model, the results show.

4.4 Class-wise Performance Metrics:

The confusion matrices in Figure summarize the performance of all models on 1383 test samples. The CNN-LSTM model has demonstrated the ability to generalize well with a high precision and recall value over significant classes of diseases, including diabetic retinopathy and infant retinal disease. CNN Model Tried Hard But Failed Certain diseases demonstrated satisfactory results but other diseases had lower sensitivity. The Autoencoder model may not effectively function as a discriminator for multi-class problems. We can use it to detect anomalies. The performance of CNN-LSTM architecture is consistent and fairly robust for all diseases classroom.

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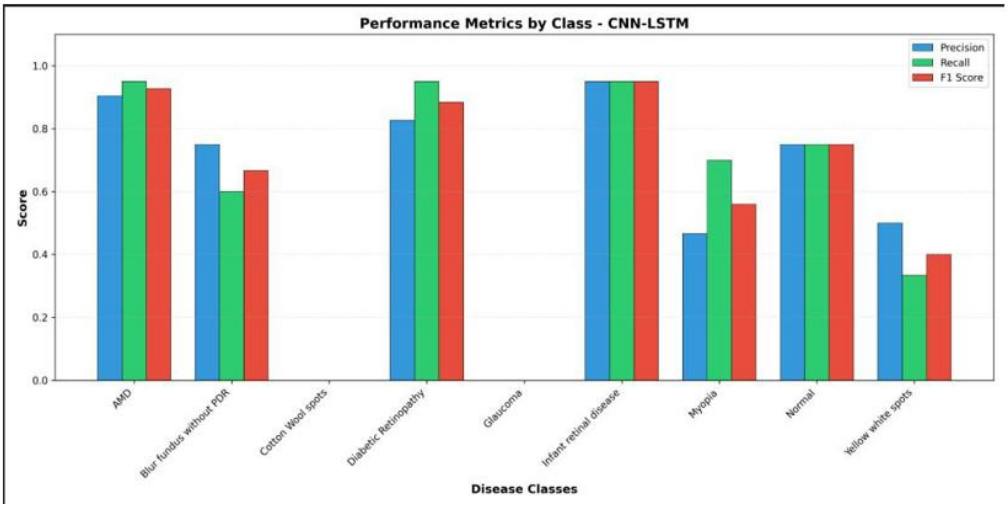
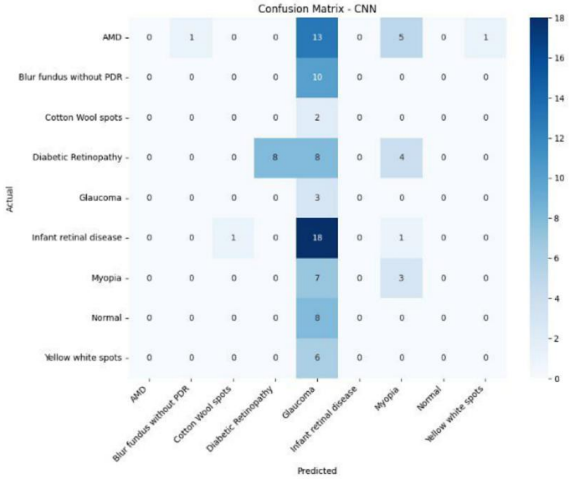


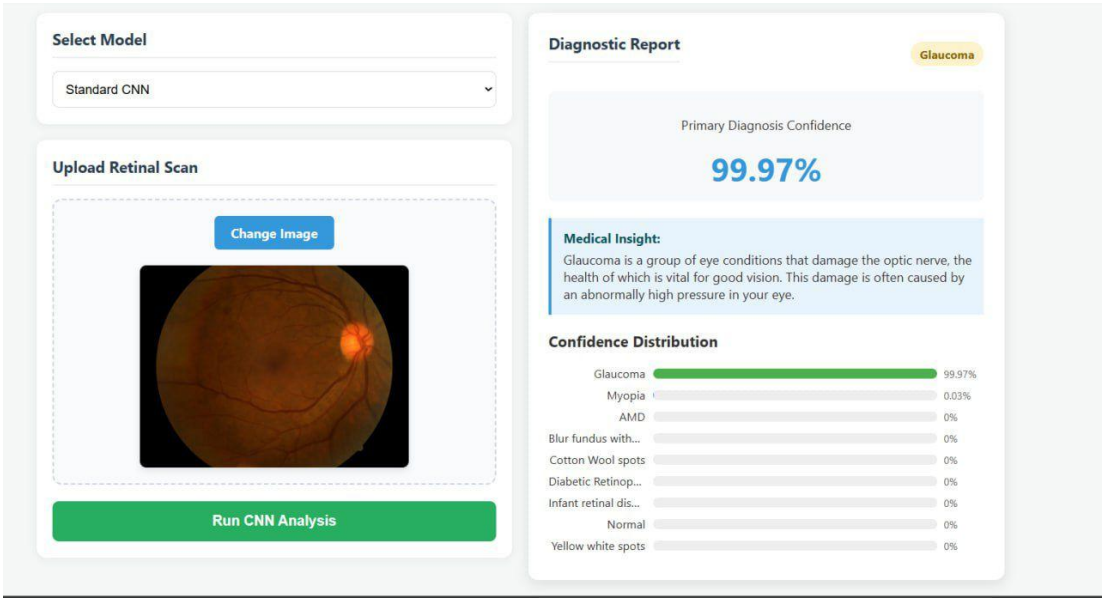
4.5 Comparative Model Performance:

The findings of the comparison of different models show that hybrid models can provide better performance than single models. In the intricate designs of the retina, differences can be subtle and CNN-LSTM can be better able to discriminate due to this hybrid property of feature extraction and sequential learning. Because it shows good performance for visually dominant differences, the basic CNN models can't extract features and generalize for diverse patterns. Autoencoder models have been utilized for the learning of latent representations.



4.6 System Output and Application Results:

The application has been created which show real time prediction diseases according the user input. The user may select the deep learning model from the drop down menu to predict the disease. The application will subsequently request the user to submit the patient's retinal scan. The system forecasts the diagnosis outcome while also providing its confidence level and medical details. The class probability distribution shown by the system prevents



hallucination of models' prediction and also judges the veracity of any model prediction like why the model predicts if the user has glaucoma or not. The proposed framework is usable as indicated by the high confidence prediction.

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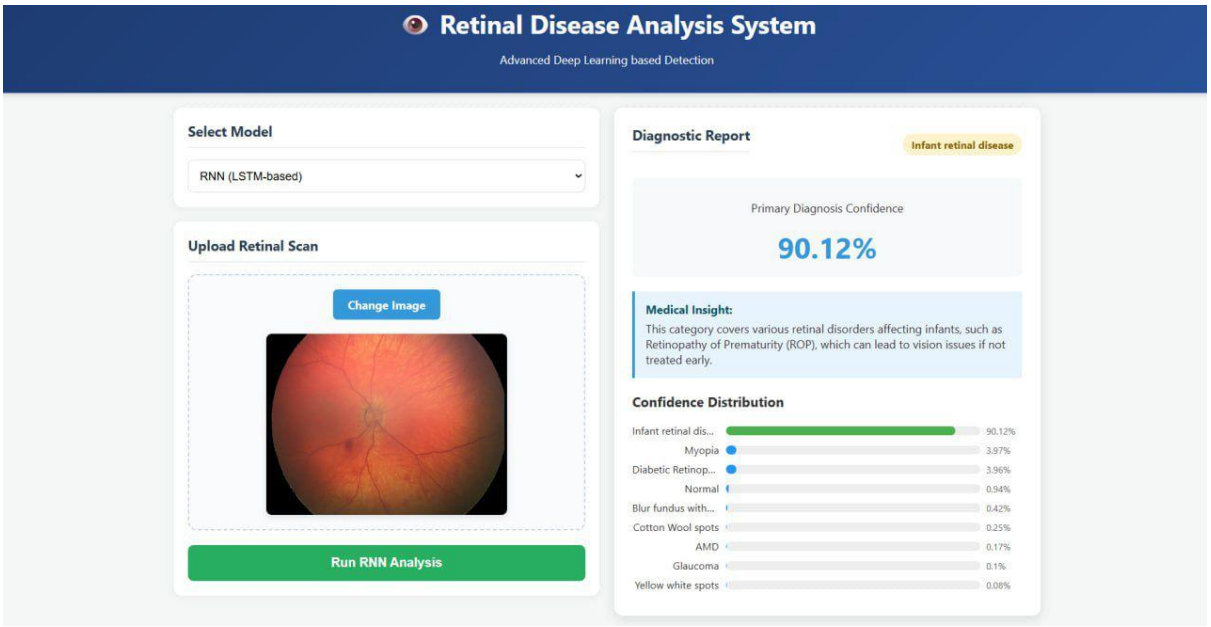

CONCLUSION

This study proposed an intelligent automated detection system of normal and pathological diabetic retinopathy using retinal fundus images. This hybrid learning model can be helpful for ophthalmologists in the screening of diabetic retinopathy. The recommended system, however, incorporates multiple deep learning structure (CNN, RNN, LSTM, GRU, Autoencoders, and VGG-16) in one application platform This enables the user to select any model of their choice for image prediction and allows them to check the performance of the model on that image interactively. The user is provided with the prediction along with its confidence of the model. It can be seen from the findings of the study conducted after various experiments that the hybrid learning models gave better results as compared to the learning models used in isolation. The CNN-LSTM design achieved superior results than either CNN or LSTM independently in certain applications. The reason for this is that it is easier for deep network to capture spatial features which helps in distinguishing similar patterns visually and learn complex patterns which are associated with these diseases and have pathological associations which are retinal in nature. The development of an Industry level application based system has been presented which integrated the state of the art hybrid deep learning architectures. This application combined various deep learning architectures and models and provided a common interactive platform to implement all these functionalities. In terms of performance, CNN-based learning architectures outperformed all other isolated learning architectures and provided better performance outcomes. The suggested CNN-LSTM produced much. This technique is likely to help with early diagnosis, which may reduce dependence on manual screening. Furthermore, it may improve access to retinal care medical services in resource-depleted areas. It must be noted that future modifications may include incorporation with clinical data-bases. There may be integration support for a multi-modal medical imaging and federated learning framework

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