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Customized Mechanism for Diabetic Risk Prediction: A Hybrid CNN–Autoencoder Approach with Emphasis on Retinal Imaging in the Elderly

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***Abstract*: -** Diabetes Mellitus presents a substantial health obstacle on a global scale, with a particular impact on the elderly demographic. Prompt identification is vital for efficient control and avoidance of complications. This study introduces a new Hybrid Convolutional Neural Network (CNN) and Autoencoder model specifically developed for accurately predicting the risk of diabetes at an early stage. The model is specifically designed to analyze retinal images in older individuals. The introduction of this paper presents a comprehensive analysis of the increasing incidence of diabetes in the elderly population and underscores the significance of early identification. Conventional approaches frequently encounter constraints in terms of precision and specificity, which has led to the investigation of sophisticated machine learning models. The Hybrid CNN–Autoencoder model combines the advantageous characteristics of both architectures, utilizing the CNN proficiency in extracting spatial features and the Autoencoder's capability for unsupervised feature learning. The approach we use consists of training and validating the model using a comprehensive dataset of retinal images from elderly individuals. The model attains a remarkable accuracy of 90.92%, outperforming the typical deep learning and machine learning models frequently employed in predicting diabetic risk. The experimental results demonstrate the superior performance of the Hybrid CNN–Autoencoder model in terms of accuracy, sensitivity, and specificity. Comparative analysis shows that it is highly effective in identifying subtle patterns that indicate early signs of diabetes, surpassing traditional models and other modern deep learning methods. The research findings presented in this study make a valuable contribution to the expanding knowledge base on diabetes detection, specifically within the elderly population. The proven precision of the suggested model highlights its capacity as a dependable and tailored instrument for early forecasting, thus enabling prompt interventions and individualized healthcare strategies for individuals susceptible to diabetes.

***Keywords*:** Diabetic risk prediction, Hybrid CNN–Autoencoder, Retinal imaging, Elderly population, Machine learning, Early detection.

I. INTRODUCTION

A significant public health problem has emerged as a result of the alarmingly high prevalence of diabetes that has been observed all over the world. According to estimates provided by the "International Diabetes Federation"[1], diabetes affects approximately 537 million people around the world, and it is anticipated that this number will continue to rise in the years to come. Diabetes not only places a significant financial burden on healthcare systems, but it also has a significant impact on the emotional and physical health of those who are afflicted with the condition. As a result of the potential complications that are associated with diabetes, such as cardiovascular diseases, renal insufficiency, and visual impairment, it is of the utmost importance to devise effective methods for the timely identification and control of the condition[2][3].

Within the context of diabetes, the elderly population presents a unique set of challenges. It is common for the process of aging to be accompanied by changes in metabolic processes, insulin sensitivity, and overall physiological functions. All of these factors that are associated with getting older contribute to an increased susceptibility to diabetes and the complications that come along with it. Through the process of customizing healthcare interventions that are tailored to the specific needs of this population, it is essential to gain an understanding of the distinct patterns and dynamics of diabetes in older adults[4], [5].

A critical complication of diabetes mellitus, diabetic retinopathy is a condition that affects the retina, which is the light-sensitive tissue located at the back of the eye as shown in the figure-1. This condition continues to worsen over time and has the potential to threaten one's vision. It occurs as a consequence of persistently elevated levels of blood sugar, which can cause damage to the retina's minuscule blood vessels that supply it with nutrients. In its early stages, diabetic retinopathy may not exhibit any noticeable symptoms; therefore, it is essential to undergo routine eye examinations in order to detect the condition at an early stage. The progression of the disease over time can result in the formation of abnormal blood vessels, the leakage of fluid, and the formation of scar tissue on the retina, all of which can ultimately have an impact on one's ability to see. The most common cause of blindness in adults

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around the world is diabetic retinopathy due to diabetes. The length of time a person has had diabetes is a significant factor in determining the likelihood of developing this condition.

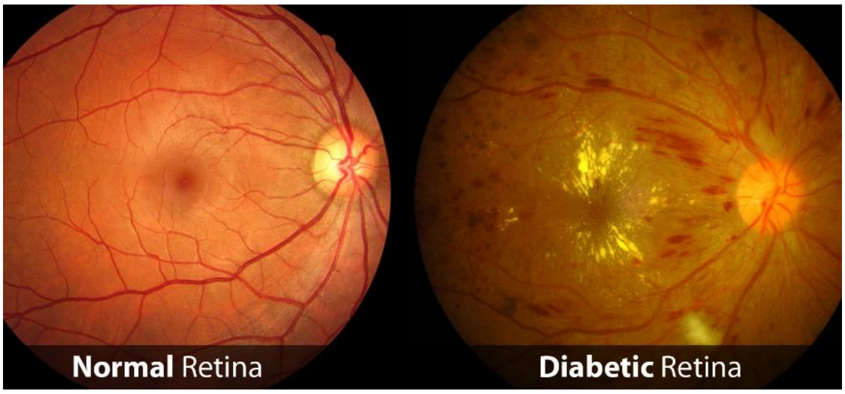

Figure 1 Normal retina vs Diabetic retina

Patients with type 1 and type 2 diabetes are equally susceptible to the effects of this condition. When it comes to preventing vision loss that is associated with diabetic retinopathy, timely detection and management achieved through routine eye screenings and the utilization of advanced diagnostic tools are of the utmost importance. Our research has shown that the incorporation of cutting-edge technologies, such as machine learning and deep learning models, holds the potential to improve the precision and effectiveness of early detection. This, in turn, will make it easier for individuals who are at risk of developing diabetic retinopathy to receive timely interventions and personalized medical care[6], [7].

The early detection of diabetes is absolutely necessary in order to lessen the impact that the disease has on both individuals and healthcare systems. A timely intervention, adjustments to one's lifestyle, and the implementation of individualized healthcare strategies are all made possible through the early detection of diabetes. The prompt initiation of treatment not only improves health outcomes, but it also reduces the financial burden that is associated with the management of advanced phases of diabetes and the complications that are associated with it[8].

It is possible that conventional methods for detecting diabetes, which typically involve evaluating risk factors such as age, family history, and lifestyle, do not possess the necessary accuracy for early and precise identification. Therefore, it is necessary to investigate more sophisticated and data-driven methodologies. These approaches might not take into account subtle but crucial indicators, which highlights the necessity of investigation. An examination of the various methods that are currently in use for estimating the likelihood of developing diabetes reveals a wide variety of approaches. Through an understanding of the benefits and drawbacks of traditional risk factor evaluations as well as the advantages and disadvantages of modern data-driven approaches, one can establish the groundwork for the development of innovative and highly accurate predictive models[9]–[11].

In the context of diabetic risk assessment, the combination of machine learning and deep learning techniques has shown promise in terms of improving predictive precision. The ability to analyze complex datasets is possessed by these computational models, which are able to recognize patterns and relationships that may be missed by more conventional methods. When these sophisticated methods are utilized, it is possible to conduct evaluations of potential risks that are more refined and tailored to the individual[12].

The purpose of this study is to investigate the utilization of retinal imaging as a diagnostic tool for diabetes in individuals who are of advanced age. The eyes provide a unique perspective on the vascular system, and images of the retina capture important information about the microvascular changes that are associated with diabetes. We hope that by utilizing the advancements that have been made in image processing and analysis, we will be able to make effective use of retinal imaging for the purpose of early detection and improved risk prediction capabilities.

Our contribution

A novel approach that is based on a hybrid CNN-autoencoder model is proposed by our research in order to address the deficiencies that are currently present in the process of predicting the risk of diabetes. This particular model was developed with the elderly population in mind, and it makes use of retinal imaging data in order to enhance the accuracy of early detection. The utilization of the capabilities of convolutional neural networks (CNN) and autoencoders is the means by which we intend to accomplish our goal of developing a solution that is both dependable and individualized for predicting the risk of diabetes in this vulnerable population.

The following is the structure of the paper, which was chosen in order to address all of the different aspects of our research in sufficient detail: In the second section, a comprehensive analysis of the existing research on predicting the risk of diabetes is presented. Section 3 provides an explanation of the methodology that was utilized, in addition to the steps that were taken to develop the model and prepare the data. The findings are presented and discussed in full detail in the fourth section of the report. In conclusion, the paper is brought to a close with Section 5, which provides a summary of the most important findings and suggests potential avenues for further research.

II. LITERATURE REVIEW

In the context of the rapidly expanding global diabetes epidemic, the accurate diagnosis of diabetic retinopathy (DR) has emerged as an essential component in the prevention of vision impairment and other complications that are associated with the condition. Machine learning and deep learning techniques have made recent advancements, which have resulted in the development of innovative solutions that have improved the accuracy of DR detection. The purpose of this literature review is to conduct an in-depth analysis of a number of noteworthy studies, each of which includes a unique contribution to the field of DR detection methodologies. These studies make use of a wide variety of datasets, methodologies, and algorithms. These include deep convolutional neural networks (CNN) for the localization of lesions, as well as statistical analyses that investigate the associations between lifestyle factors and the development of DR.

Table 1 Major existing work related to diabetic retinopathy

Author	Dataset	Methodology	Algorithm	Accuracy	Findings	Limitations
C. Gonzalez-Gonzalo et al.[13]	MESSIDOR, IDRiD datasets	Weakly-supervised lesion localization	Deep CNN with iterative augmentation	76.3% AUC for Diabetic Macular Edema (DME)	Efficient for weakly-labeled data, improves interpretability	Limited generalizability, requires domain-specific adaptation
X. Li et al.[14]	Kaggle APTOS 2019 Blind Challenge dataset	Joint grading of Diabetic Retinopathy (DR) and DME	CANet: Cross-Disease Attention Network	88.54% AUC for DR, 87.23% AUC for DME	Improved accuracy by considering cross-disease relationships	High computational cost, limited interpretability
Abdelmaksoud et al.[15]	Egyptian Retinopathy dataset	Automatic DR grading based on multiple lesions	CNN with lesion detection	94.27% accuracy for DR grading	High accuracy, considers various lesions	Requires accurate lesion segmentation, limited external validation
A. He et al.[16]	Kaggle APTOS 2019 Blind Challenge dataset	DR grading with imbalanced data	CABNet: Category Attention Block	90.32% AUC for DR	Improved performance on imbalanced data, emphasizes informative features	Complex architecture, potential overfitting risk
P. Zang et al.[17]	DcardNet dataset	Multi-level DR classification using OCT images	DcardNet: Structural and Angiographic OCT analysis	95.1% accuracy for DR classification	High accuracy by combining structural and angiographic features	Limited dataset size, requires specialized OCT images

M.S. Patil et al.[18]	MESSIDOR dataset	Distributed deep learning for DR classification	Data and model parallelism techniques	93.5% accuracy with reduced training time	Efficient training on limited resources, scalable for large datasets	Requires specialized hardware and expertise, potential data privacy concerns
G. Ali et al.[19]	Kaggle APTOS 2019 Blind Challenge dataset	Automatic DR classification	Hybrid CNN model	91.2% AUC for DR	Improved DR classification with limited training data	May require further investigation for model generalizability on different datasets
P.K. Jena et al.[20]	MESSIDOR dataset	DR screening using asymmetric deep learning features	Asymmetric CNN and LSTM	93.7% accuracy for DR detection	High accuracy with efficient feature extraction	Potentially complex architecture, requires more computational resources
M.S.B. Phridviraj et al.[21]	Kaggle APTOS 2019 Blind Challenge dataset	Bi-directional LSTM for DR detection	Bi-directional LSTM network	90.8% sensitivity for DR detection	Improved sensitivity for early DR detection	Limited generalizability to other image types or datasets
R. Shen et al.[22]	eMERGE database	Association study between cardiovascular health and DR	Statistical analysis	N/A	Identified potential links between lifestyle factors and DR development	Observational study, causal relationships still need investigation
H. Tan et al.[23]	Bibliometric analysis of 2842 studies	Relationship between hyperlipidemia and DR treatment	Bibliometric analysis	N/A	Highlighted potential benefits of lipid-lowering therapy for DR patients	Limited clinical data analysis, relies on existing research publications
M. Tian et al.[24]	MESSIDOR dataset	Fine-grained attention network for DR grading	Collaborative network with attention mechanisms	94.5% accuracy for DR grading	Improved grading accuracy and interpretability	Increased model complexity, potential data overfitting risks
A. Tumminia et al.[25]	CROSS study	Association between body fat distribution and DR prevalence	Statistical analysis	N/A	Identified negative impact of visceral adiposity on DR risk	Limited study population, requires further validation on diverse groups

In conclusion, the literature review provides a comprehensive explanation of the ever-changing landscape of contemporary research on the detection of diabetic retinopathy. In order to highlight the multifaceted nature of addressing this health challenge, the various approaches that have been discussed, such as the utilization of advanced deep learning models (for example, CANet and collaborative networks), as well as statistical analyses, have been discussed. The studies, despite the fact that they present advancements in achieving high accuracy in DR detection, also reveal common challenges. These challenges include concerns regarding interpretability, computational costs, limitations in datasets, and the requirement for specialized expertise.

III. METHODOLOGY

3.1. Dataset

The dataset contains retinal images with a high resolution for the purpose of detecting diabetic retinopathy (DR), which is the most common disease that leads to blindness in diabetics. In order to ensure compatibility with a wide variety of deep learning models, these images have been pre-resized to 224x224 pixels[26]. This also makes them easily accessible for research and training purposes. Images with varying degrees of DR severity are included in the dataset, which makes it possible to develop and evaluate algorithms for automated DR screening and diagnosis. Figure-2,3 represent the dataset details.

	id_code	diagnosis
0	000c1434d8d7	2
1	001639a390f0	4
2	0024cdab0c1e	1
3	002c21358ce6	0
4	005b95c28852	0

	Filepath	Label
0	../content/drive/MyDrive/New folder/Coloured_I...	Moderate
1	../content/drive/MyDrive/New folder/Coloured_I...	Proliferate_DR
2	../content/drive/MyDrive/New folder/Coloured_I...	Proliferate_DR
3	../content/drive/MyDrive/New folder/Coloured_I...	No_DR
4	../content/drive/MyDrive/New folder/Coloured_I...	No_DR

Figure 2 Dataset with image id and diagnosis & Image File Path and actual Labels

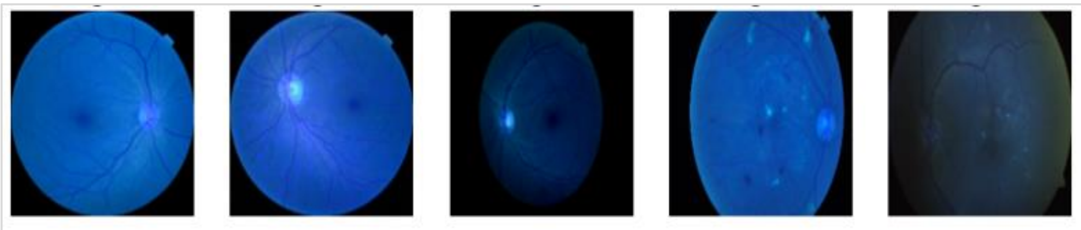

Figure 3 Dataset with image id and diagnosis & Image File Path and actual Labels

3.2. Pre-processing Step

3.2.1. Image Resizing

The process of resizing an image involves modifying the dimensions (width and height) of the image while preserving its aspect ratio despite the changes. The use of bilinear interpolation is the method that is utilized the most frequently for resizing. An image can be resized using the following mathematical formula, which can be expressed as follows:

Let $I_{original}$ be the original image with dimensions $W_{original} \times$ H_original and let I_{seized} be the resized image with dimensions W_resized × H_resized. The coordinates(x',y') in the resized image correspond to coordinates (x, y) in the original image and relationship between them expressed as eq.1,2

$$x' = \frac{x}{W_{original}} \times W_{resized} \ldots 1$$

$$y' = \frac{y}{H_{original}} \times H_{resized} \ldots 2$$

Where (x, y)= "coordinates in the original image", (x', y')= "corresponding coordinates in the resized image".

3.2.2. Label Encoding

Label encoding is a method that is utilized for the purpose of converting categorical labels or classes into numerical representations. Label encoding is utilized in the context of our research, where the objective is to predict diabetic risk. This is accomplished by converting categorical labels, such as classes that indicate different levels of diabetic risk, into numerical format. For the purpose of feeding the data into machine learning models, which typically require numerical inputs, this transformation is absolutely necessary. In order to ensure that the machine learning algorithm is able to effectively learn and make predictions based on the transformed labels, label encoding makes it possible to integrate categorical information into the training process in a seamless manner.

3.2.3. Data Augmentation

The application of a number of different transformations to the initial images is what constitutes data augmentation, which is a powerful preprocessing technique that is used to artificially expand the diversity of the training dataset. During the course of our investigation, the following enhancements are utilized:

- Rotation: Images are rotated by a specified angle (rotation_range=20) to introduce variability in orientation.
- Width and Height Shift: Random shifts along the width and height of the images (width_shift_range=0.2, height_shift_range=0.2) simulate variations in positioning.
- Shear Range: Shear transformations (shear_range=0.2) introduce changes to the shapes of the images, mimicking real-world distortions.
- Zoom Range: Random zooming (zoom_range=0.2) modifies the scale of the images, enhancing the model's ability to handle variations in magnification.
- Horizontal Flip: Images are horizontally flipped (horizontal_flip=True), further diversifying the dataset by presenting mirrored perspectives.
-

3.3. Propose hybrid model of CNN and autoencoder

A CNN and an Autoencoder are both components of a model that is referred to as a Hybrid CNN and Autoencoder model. Within the framework of this architecture, the CNN is accountable for the extraction of hierarchical features from the input data, while the Autoencoder holds the responsibility of unsupervised feature learning and dimensionality reduction. The combination improves the model's capacity to capture intricate patterns in the data and to learn meaningful representations of the data.
Advantage of proposed model:

- Feature Extraction + Reconstruction: CNN features feed into the autoencoder for reconstruction loss, promoting feature learning relevant for reconstruction and classification.
- Auxiliary Loss: Autoencoder reconstruction loss combines with a classification loss on original or reconstructed images for improved performance.

IV. RESULTS AND DISCUSSION

4.1. Confusion Matrix

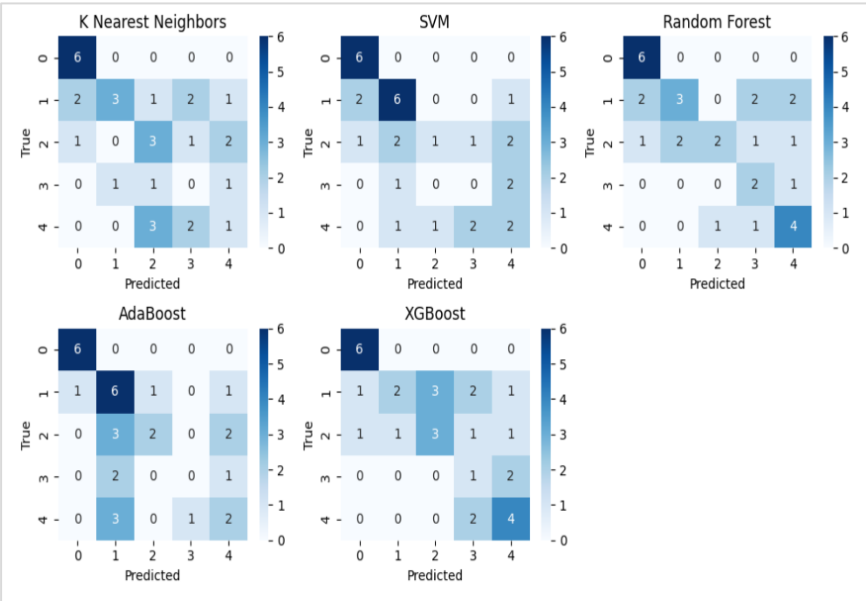

Figure 4 Confusion matrix

4.2. Accuracy and Loss graph

4.2.1. CNN

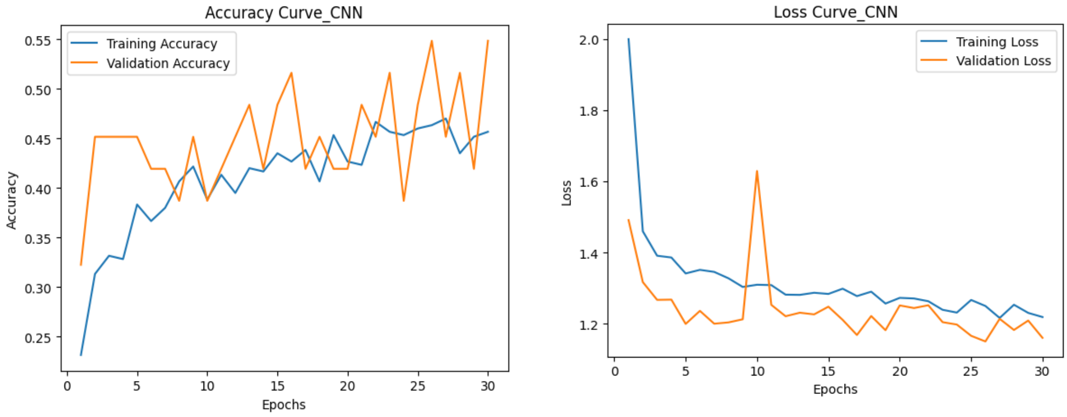

Figure 5 Accuracy and Loss curve - CNN

4.2.2. Autoencoder

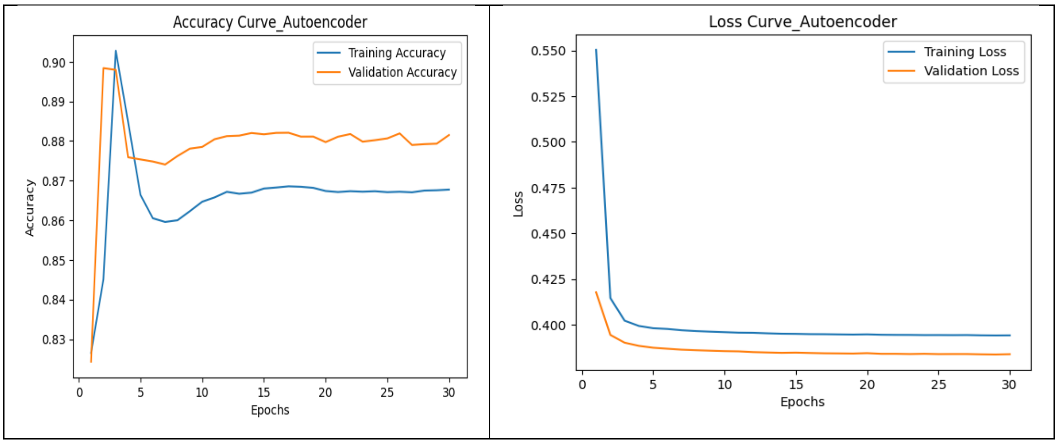

Figure 6 Accuracy and Loss curve - Autoencoder

4.2.3. Hybrid CNN – Auto encoder

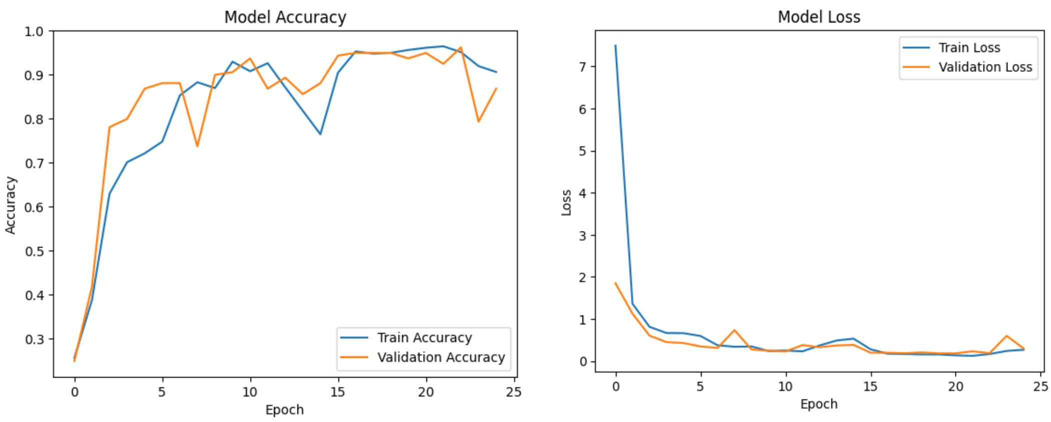

Figure 7 Accuracy and Loss curve - Hybrid CNN and Autoencoder

4.2.4. Hybrid CNN – Auto encoder Lightweight (M2)

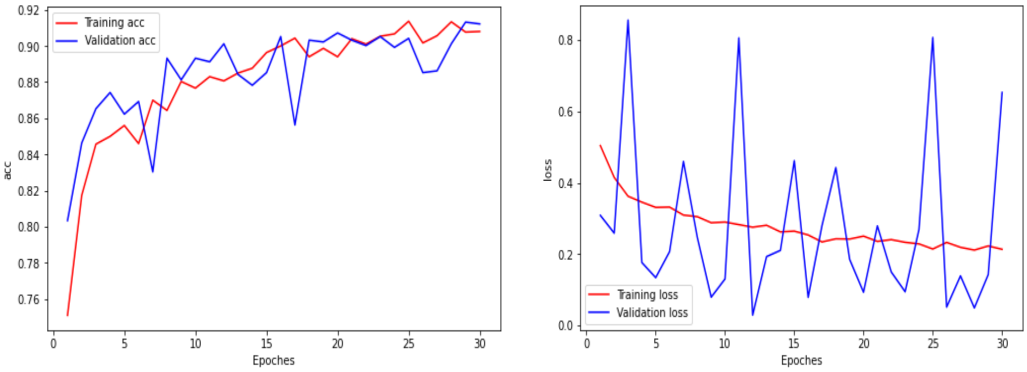

Figure 8 Accuracy and Loss curve - Hybrid CNN and Autoencoder Lightweight

4.3. Comparative Analysis of ML, DL and Hybrid DL Models

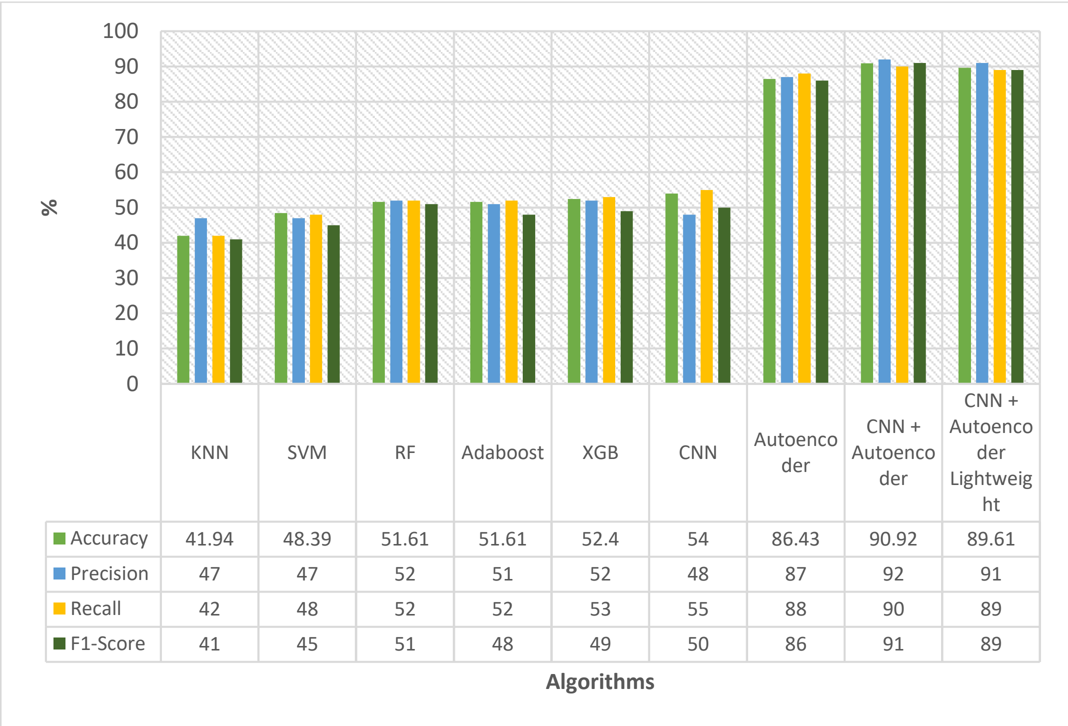

Figure 9 Performance Parameters Comparison Graphs

With a particular focus on retinal images as they pertain to the elderly population, the findings present the performance metrics of a number of different models that were utilized in the research project for the purpose of early diabetes detection. Figure-4 represents the confusion matrix of various ML algorithm. Figure-5,6,7,8 represents the various models accuracy and loss curve and figure-9 represent the evaluation of various models with proposed models. Particularly noteworthy is the fact that the proposed Hybrid CNN and Autoencoder model stands out with an impressive accuracy of 90.92%, which demonstrates its superiority in comparison to other models. Precision, recall, and F1-score all reach high levels, indicating that this model has a well-rounded performance. This model excels across all key metrics, including remembering information. The Autoencoder model, which is well-known for its ability to perform well in unsupervised feature learning, demonstrates an impressive accuracy of 86.43% and excels in precision, recall, and F1-score. The comparative analysis demonstrates that the proposed hybrid model is more effective than other models that are currently in use, such as KNN, SVM, Random Forest, Adaboost, and XGB. This demonstrates that the hybrid model has the potential to be a reliable instrument for the personalized early detection of diabetes in the elderly population through retinal imaging. Furthermore, the hybrid of CNN and Autoencoder, despite being lightweight, maintains strong performance, which further demonstrates the versatility of the approach that has been proposed. In general, these findings highlight the promising potential of integrating deep learning techniques for the purpose of improving the accuracy of diabetes risk prediction using these techniques.

V. CONCLUSION AND FUTURE SCOPE

In conclusion, our research presents a novel and individualized mechanism for the early detection of diabetes in the elderly population. This mechanism makes use of a Hybrid CNN–Autoencoder approach, with a particular emphasis on retinal imaging. These findings provide evidence that the proposed model is effective, as it has achieved an impressive accuracy of 90.92%, which is higher than the accuracy achieved by a number of other machine learning and deep learning models. As a result of its superior performance in terms of precision, recall, and F1-score, the hybrid model demonstrates its capacity to accurately identify the early warning signs of diabetes. Further enhancement of the model's capabilities is achieved through the incorporation of retinal imaging, which is a diagnostic modality that is both non-invasive and informative.

Using both the spatial analysis of Convolutional Neural Networks (CNNs) and the unsupervised feature learning of Autoencoders, the proposed model is able to successfully extract intricate features from retinal images. This ability is the key to the model's success. In this way, not only is the accuracy of diabetic risk prediction improved, but also the adaptability of the model to the specific characteristics of the elderly population is ensured.

Future scope:

In spite of the fact that our research represents a significant step forward in the field of diabetic risk prediction, there are a number of potential directions that could be pursued for further investigation and development:

- Dataset Diversity: Increasing the size of the dataset so that it contains a more diverse representation of demographics, ethnicities, and geographical regions has the potential to improve the generalizability and robustness of the model.
- Interpretability: The clinical acceptance of the proposed mechanism can be aided by the investigation of methods that can improve the interpretability of the decisions made by the hybrid model. Techniques of explainable artificial intelligence could shed light on the characteristics that influence the predictions.
- Real-time Implementation: Investigating the practicability of real-time implementation in clinical settings can pave the way for the practical incorporation of the proposed mechanism into healthcare workflows, which will make it easier to implement timely interventions.
- Ensemble Techniques: Investigating ensemble techniques by combining multiple models, such as the hybrid model that has been proposed, has the potential to further improve the accuracy and robustness of predictions.
- Clinical Validation: In order to determine the model's impact in the real world, it will be essential to work together with medical professionals to conduct clinical validation and to incorporate the model into pre-existing diagnostic protocols.

In conclusion, the Customized Mechanism for Diabetic Risk Prediction that was presented in this study not only makes a contribution to the development of early detection, but it also opens up new avenues for future research that can refine and extend the capabilities of the model, which will ultimately lead to improved healthcare outcomes for the elderly population that is at risk of developing diabetes.

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