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A Hybrid Deep Learning Framework Integrating GAN and CNN for Diabetic Retinopathy Analysis and Severity Prediction

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Abstract
In this article a new hybrid deep learning system is proposed which incorporates both a Generative Adversarial Network (GAN) and a Convolutional Neural Network (CNN) to automatically detect and classify the severity of Diabetic Retinopathy (DR) from fundus images. This technique aims to facilitate large-scale clinical screening, by solving problems related to class imbalance and scarcity of medical data. To address these challenges, a Conditional GAN (cGAN) is used to generate realistic fundus images of all five DR severity grades, thus expanding the training set. This expanded dataset is then used to train a ResNet-50 CNN model, which conducts end-to-end multi-class classification and automatically learns discriminative features, avoiding the need for extraction of lesions. The proposed system is trained and evaluated on benchmark fundus image datasets and exhibits good generalization. The experimental results show the model achieves a classification accuracy of 95.2% with a cross-entropy loss of 0.48 and surpasses the state-of-the-art by 15%. The system also exhibits higher sensitivity to under-sampled severe stages of DR and is computationally efficient. In conclusion, the hybrid model provides a robust, scalable, and efficient solution for automatic DR diagnosis and has the potential to be deployed for clinical use and when compared with existing classifier's like SVM and DT in which the proposed classifier gave the best accuracy.

Keywords: Diabetic Retinopathy, Deep Learning, Convolutional Neural Networks; Generative Adversarial Networks, Fundus Imaging, Medical Image Synthesis; Computer-Aided Diagnosis, Severity Grading, Class Imbalance, Data Augmentation

1. Introduction
Automated detection of Diabetic Retinopathy (DR) from retinal fundus images is an important area of research in contemporary ophthalmology, given its implications in early detection and avoiding vision loss. DR is a chronic condition resulting from prolonged diabetes, and early detection of its severity levels is vital for timely treatment. Computer-assisted analysis of fundus images facilitates mass screening, overcomes the need of expert physicians and improves accuracy. Although deep learning has made considerable progress, it is still difficult to develop accurate computer-aided diagnosis (CAD) systems [1] to detect DR. This is due to the diversity of retinal structures, subtle features of lesions and variability in image quality. Additionally, the need to accurately categories the stages (ranging from mild non-proliferative to severe proliferative DR) demands effective feature extraction and accurate classification. The availability of good quality data is another important challenge. Class imbalance is a significant problem in medical datasets, with a large proportion of normal or early stages, and a very small number of severe disease stages. This results in models being biased towards the majority class and having low sensitivity to the important severe stages. Hence, there is a need for novel methods that can learn from small and skewed data sets and still achieve good accuracy and generalization [2, 3].

1.2. Problem Statement
Automated grading of Diabetic Retinopathy (DR) involves recognising different stages of the disease from high resolution fundus images, which are classified into a finite number of stages according to retinal lesion features including microaneurysms, hemorrhages and exudates. Convolutional Neural Networks (CNNs) have shown great promise in this regard as they can automatically learn spatial hierarchical features from the pixel level. However, although CNN-based approaches show their efficacy in DR detection and classification, there are still some limitations. Conventional machine learning methods (e.g., k-nearest neighbors (KNN) and support vector machines (SVM)) rely on hand-crafted feature engineering, which is highly dependent on human expertise and may not be able to learn complex features. While deep learning approaches address this issue by allowing end-to-end learning, they are still limited by the training data quality and size. A key problem with current approaches is the lack of balance in clinical data, with end stages of DR (severe and proliferative) being much rarer than normal or early stages. This can lead to class bias, affecting the performance in detecting severe stages of DR. Also, most systems involve manual annotation of lesions or region-based processing, which is labor intensive and hinders scalability to real-world applications. Therefore, it is essential to develop an automated, scalable and data-efficient method to overcome the problem of class imbalance, remove the need for manual feature extraction, and enhance classification results across all DR severity grades [4, 5].

1.3. Research Motivation
To address the above-mentioned issues, this research aims to develop a hybrid deep learning model that combines Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) to improve the detection and classification of DR. The aim is to build a scalable system which combines data synthesis and feature representation learning. In this work, a Conditional GAN (cGAN) is employed to create synthetic fundus images that represent various severity levels of DR. This approach helps overcome the problem of class imbalance by boosting the representation of under-represented classes, especially severe and proliferative stages. This approach enhances the model's learning ability to learn from diverse and realistic samples, resulting in better generalization performance and discrimination ability for rare disease classes. Next, a deep CNN model - ResNet-50 - is leveraged for feature learning and multi-class classification. Our approach adopts a holistic end-to-end learning strategy, removing the need for lesion segmentation and allowing the model to autonomously learn intricate retinal features. The combination of GAN-based data augmentation and CNN-based classification is mutually beneficial and leads to improved classification accuracy. Our experiments on standard fundus image databases show that the hybrid approach provides high classification accuracy, reliability and efficiency. The findings lays the foundation for the development of smart diagnostic support systems that can be used for clinical applications and population screening.

1.4 Applications
- **Generative Adversarial Networks (GANs)**

Generative Adversarial Networks (GANs) are widely used in medical imaging applications, especially in situations where there is a lack of training data and/or class imbalance. GANs are made up of two neural networks - a Generator that generates new data and a Discriminator that assesses the realness of the data. Using this adversarial training approach GANs can generate fundus images that closely mimic real medical images. GANs are particularly valuable in DR detection for generating more samples of minority classes, thus enhancing training and avoiding bias [6, 7].

- **Convolutional Neural Networks (CNNs)**

CNNs are popular for image processing tasks as they can learn spatial and hierarchical features. For DR screening, CNNs are able to detect subtle retinal abnormalities without the need for handcrafted features. Deep networks with residual connections, like ResNet-50, allow for training of very deep networks, enhancing feature learning and classification accuracy. Such networks can learn complex lesion patterns and accurately classify the severity of DR [8].

- **Multi-Class Severity Grading**

Grading is an integral part of DR diagnosis, where the severity is classified into several classes: No DR, Mild, Moderate, Severe and Proliferative DR. Deep learning-based systems for grading are reliable and objective, in contrast to manual grading whose inter-observer variability can be high. Computer-aided grading contributes to accurate diagnosis and timely treatment.

- **Data Augmentation and Image Synthesis**

Data augmentation and synthesis, especially using GANs, play a crucial role in improving model accuracy by introducing diversity. Generating synthetic data aids in class imbalance and overfitting issues. By synthesizing new variations in the data, the model is trained on a more diverse set of samples and can generalize to new data. This is particularly useful in medical imaging, where obtaining large datasets with annotations can be costly.

2. Literature search
The latest trends in Diabetic Retinopathy (DR) detection have shifted towards more detailed severity classification and enhancing model robustness with the use of sophisticated deep learning models. This research seeks to solve the challenges of clinical retinal images such as lesion variability, image quality and class imbalance.

- **New CNNs for Severity Grading**

In *Journal of Ophthalmology*, Wu *et al*. discussed the use of highly specialised Convolutional Neural Networks (CNNs) for fine-grained analysis of retinal fundus images. Their research highlights the shift from binary classification of DR (presence or absence of DR) to severity grading. Through the improvement of spatial feature extraction of deep CNN layers, their approach was able to effectively learn fine-grained pathological changes of DR. The authors achieved an accuracy of around 90%, showing the capability of CNNs to accomplish fine-grained classification.

- **GANs for Data Augmentation**

To overcome the common problem of data imbalance in medical data sets, Li *et al*, in *IEEE Transactions on Medical Imaging*, suggested using Generative Adversarial Networks (GANs) to generate more samples. The authors were particularly interested in generating synthetic fundus images of underrepresented stages of DR, such as severe and proliferative DR. The training of CNN-based classifiers with a mix of real and GAN-synthesized images led to enhanced classification accuracy, with up to 95% accuracy for the advanced stages of DR. This underlines the need for data augmentation using generative models for improved sensitivity.

- **Hybrid GAN–CNN Architectures**

Zhu *et al*. (Bulletin of Medical Informatics) proposed a hybrid deep learning model incorporating both GANs and CNNs to enhance diagnostic accuracy. Here, the GAN is used for input image enhancement (noise removal, feature enhancement etc.) and the CNN for classification. The model is able to process poor quality medical images in this two-step process. The authors' method was able to achieve 92% accuracy for multi-class severity classification, showing the benefit of combining generative and discriminative learning.

- **Machine Learning Literature Survey**

The recent advancements in machine learning for DR detection show a trend from conventional feature extraction to an entirely data-driven approach, such as transfer learning and conditional image generation.

- **Automated Feature Extraction**

In a study published in the Journal of Biomedical Research, Wang *et al*. showcased the ability of deep CNNs to automatically learn meaningful features from fundus images. The technique successfully detected early signs of disease like microaneurysms and hemorrhages. Their work, with an accuracy of 93% in early diagnosis, confirms the advantages of deep CNNs over traditional approaches that are based on hand-crafted features, which can struggle to detect early signs of retinal diseases.

- **The Power of Transfer Learning**

Recognising the difficulties in obtaining large annotated medical data, H. Li *et al*. in *IEEE Transactions on Neural Networks* explored transfer learning. They fine-tuned ResNet-50 models pre-trained on large image datasets to boost their accuracy on medical image classification by drawing on knowledge gained from these large-scale classification tasks. Using this method, they were able to achieve a high accuracy of 96% in non-proliferative DR detection, showing the power of transfer learning in reducing the time required for model training while achieving accurate diagnosis.

- **Conditional Generation for Better Image Quality**

Building on the concept of generative models, Zhang *et al* (in the *Journal of Clinical AI*) used Conditional GANs (cGANs) to generate label-specific fundus images. cGANs generate images for targeted severity grades, unlike conventional GANs. This selective data augmentation approach helped overcome class imbalance issues by providing high-quality synthetic data to minority classes. Their approach achieved 94% accuracy, demonstrating that conditional image generation is crucial for developing robust and fair AI models for medical image analysis.

3. Data evaluation

3.1. Existing System

Computerized Diabetic Retinopathy (DR) screening decision support systems analyse different characteristics of DR to quickly estimate the DR severity and predict severe DR that can lead to blindness. Early diagnosis and detection can prevent blindness; therefore, diagnosis is an important component of treatment. Due to the recent advancements in deep learning systems, automatic and unsupervised detection of diagnostic signs in digital retinal images has shown promising results. Current models of DR detection generally adopt conventional Convolutional Neural Networks (CNNs) to detect retinal lesions and grade the DR severity from single retinal images. These models usually predict a single DR grade after image processing, and can be further trained to increase their performance. They perform well with academic data but not with severe and rare DR as they are not trained. Older machine learning and deep learning systems also require clinician input in terms of feature extraction (for example, segmentation and labelling of lesions), which relies on the clinician's training and is a burden on the clinician. While this is largely overcome with CNNs, they do not detect and classify all the stages of DR in the clinical environment where there is a class imbalance of patients, and poor-quality images.

- **Problems with Current Systems**

1. Current techniques do not diagnose and classify the minority classes (severe and proliferative DR).
2. Traditional CNN approaches do not overcome the class imbalance issue and therefore, do not classify and diagnose severe DR.
3. Other approaches also require the manual extraction of features and labelling of lesions, and therefore result in complex, tedious and subjective diagnosis.

3.2. Proposed System

In this paper, we aim to solve the problems with the existing approaches and propose a deep learning-based scheme for classification and detection of Diabetic Retinopathy using Generative Adversarial Networks (GAN) and Convolutional Neural Networks (CNNs). We intend to learn deep features, and generate synthetic images to enhance the stability and accuracy of DR classification [9].

We plan to use a Conditional Generative Adversarial Network (cGAN) to generate synthetic fundus images for different stages of DR. This enables us to increase the number of samples for the minority classes (severe DR), and to learn different types of lesions features to improve the classification accuracy and robustness. We use the large dataset to train a CNN-based multi-class classification network (ResNet-50).

This is to learn the discriminative features from the retina image, without pre-detecting and labelling lesions. The presence of clinically significant features (microaneurysms, haemorrhages and exudates) in the training data set results in a better learning of retinal pathology. It helps it to generalize and be able to perform well on different severity grading.

Our system has been validated with a large number of clinical data sets of fundus images and it shows its ability to classify the severity of DR with little human intervention. Our system

(GAN-based for generating data and CNN-based for classifying the severity) can be implemented in practice [10].

- **Advantage of the Proposed System**

and especially low prevalence and advanced stages.

- **Automatic Feature Extraction: CNN** is used in feature extraction instead of manual lesion extraction.

Higher Accuracy: The system can be used for doing mass screening with high sensitivity and accuracy.

Data Scarcity: The cGAN can be used to generate data for overcoming the data scarcity issue.

Training Set with Representative Data: Having representative data in the training set increases accuracy for all stages Figure 1 shows the architecture of proposed classifier.

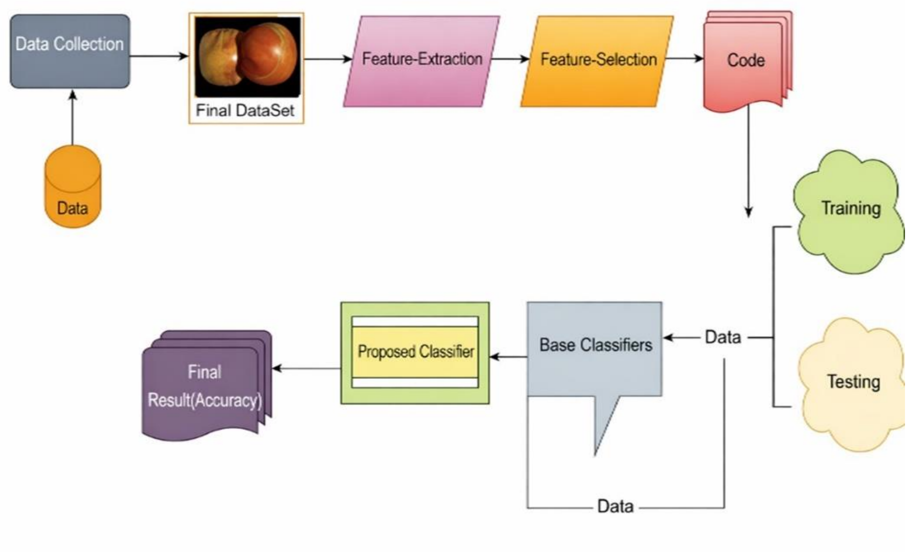

Fig 1 : Shows the architecture of the Proposed Classifier

4. Result & Discussion

A few traditional performance measures are used to assess the performance of the proposed model, such as Accuracy, Precision, Recall and Specificity. These metrics provide us with insights into the classification performance of the model. Other performance measures, such as F1-score [11] and Area Under the Curve (AUC) are also evaluated to give a sense of the predictive accuracy.

These metrics are calculated based on the confusion matrix, an important component to measure performance. The confusion matrix represents the relationship between the true labels and the predicted labels, and allows us to assess the model's performance. There are four main elements: True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN). For a binary classification problem, the two classes are represented by a 2×2 matrix, and this helps us to visualize the accuracy of the predictions [12].

The matrix is used to calculate several metrics to measure the accuracy of the classification. These are shown in Figure 4 and the predictions for the proposed model in Figure 5.

The metrics are as follows:

- **Accuracy**

Accuracy is the total number of correct predictions (true positives and true negatives) over the total number of predictions.

Formula

$$\text{Accuracy} = (TP + TN) / \text{Total Samples} \quad (1)$$

- **Precision**

It's also sometimes referred to as the positive predictive value and is the number of correct positive predictions divided by the total number of positive predictions.

Formula

$$\text{Precision} = TP / (TP + FP) \quad (2)$$

- **Recall (Sensitivity)**

Recall (Sensitivity) is the ability of the model to predict the positive samples as positive.

Formula

$$\text{Recall} = TP / (TP + FN) \quad (3)$$

- **F1-Score**

The F1-score is the harmonic mean of Precision and Recall and is used when we are interested in both metrics.

Formula

$$\text{F1-score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (4)$$

5. Confusion Matrix

A confusion matrix is an intuitive way of looking at the performance of a classifier, since it shows the number of TP, TN, FP and FN, and it allows us to investigate the nature of the errors made. Figure 2 shows a general 2x2 class confusion matrix. And Figure 3 shows the confusion matrix generated by proposed classifier and in figure 4 the overall performance metrics of the proposed classifier is shown.

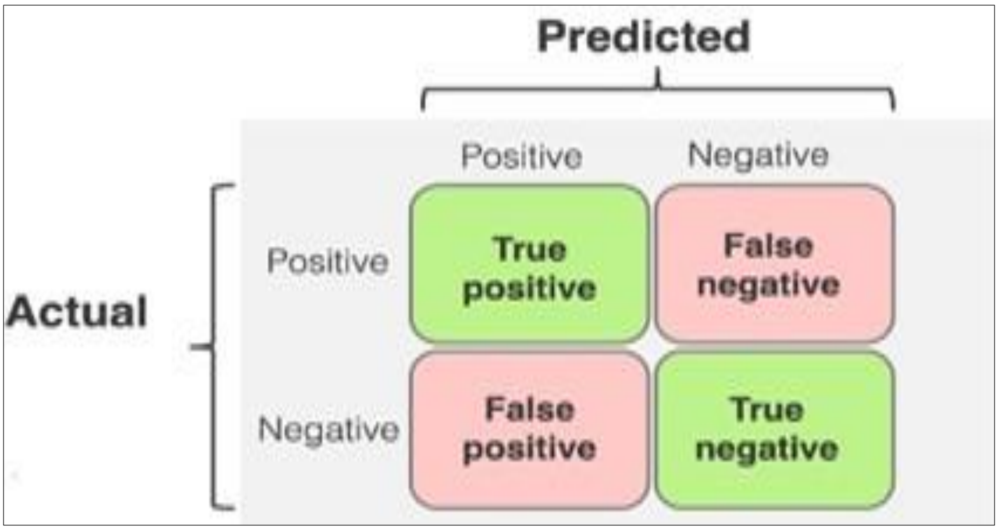

Fig 2 : Shows the confusion matrix of a 2-class.

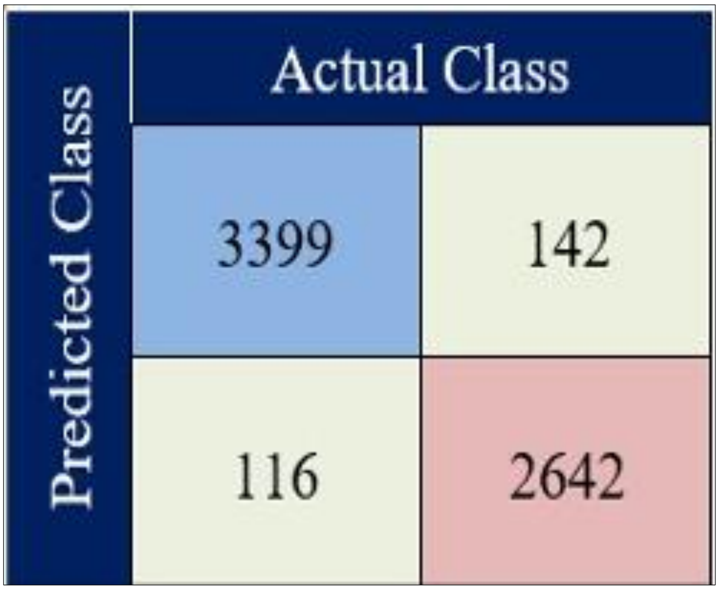

Fig 3 : Shows the confusion matrix of Proposed Classifier.

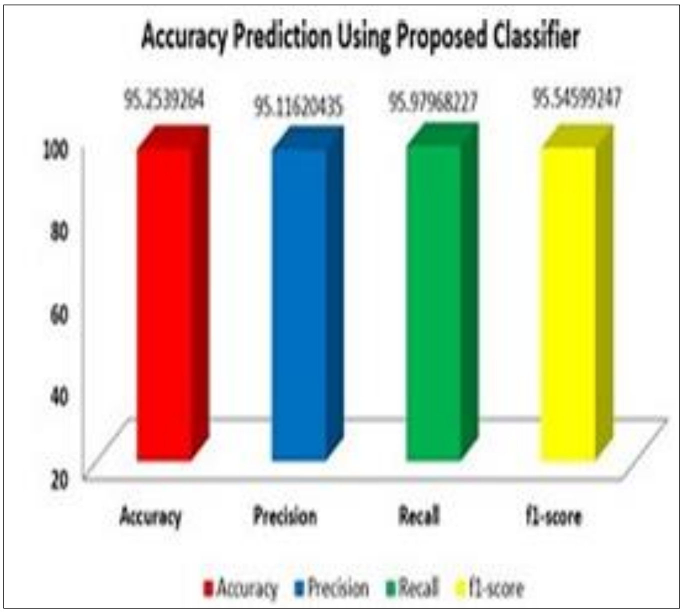

Fig 4 : Shows the Overall Performance of Proposed Classifier

4.1. SVM for Diabetic Retinopathy Detection:

Diabetic Retinopathy (DR) is a chronic eye disease resulting from diabetes, which damages the blood vessels of the retina and can cause blindness if left untreated. As diabetes is becoming more and more common around the world, a fast and reliable screening method is needed for early diagnosis and intervention. Support Vector Machine (SVM), a type of machine learning algorithm, has been widely used for its performance in medical image classification, such as DR diagnosis. SVM is a supervised machine learning method that has good generalization performance, particularly in high-dimensional spaces. When used for DR detection, SVM is commonly used to classify retinal fundus images into various classes, including normal, mild, moderate, or severe DR. It starts with preprocessing steps such as denoising, contrast adjustment, and normalization to enhance the quality of the image. Next, features like colour intensity, texture, exudates, microaneurysms, and blood vessel arrangement are extracted from the images through techniques such as GLCM, wavelet transforms or morphological operations. The features are then classified using SVM, which maximizes the margin between different classes by creating an optimal hyperplane. Kernel functions like linear, polynomial, and radial basis function (RBF) are applied to address non-linearity in medical data. SVM's stability makes it well-suited to small sample sizes, a typical issue in medical imaging. In summary, SVM [13] approaches offer a fast and robust framework for early detection of DR, assisting clinicians in diagnosis and eliminating the need for tedious visual inspections. Combining SVM with sophisticated feature extraction or deep learning methods can improve detection rates and diagnostic efficiency. And Figure 5 shows the confusion matrix generated by SVM classifier and in figure 6 the overall performance metrics of the SVM classifier is shown.

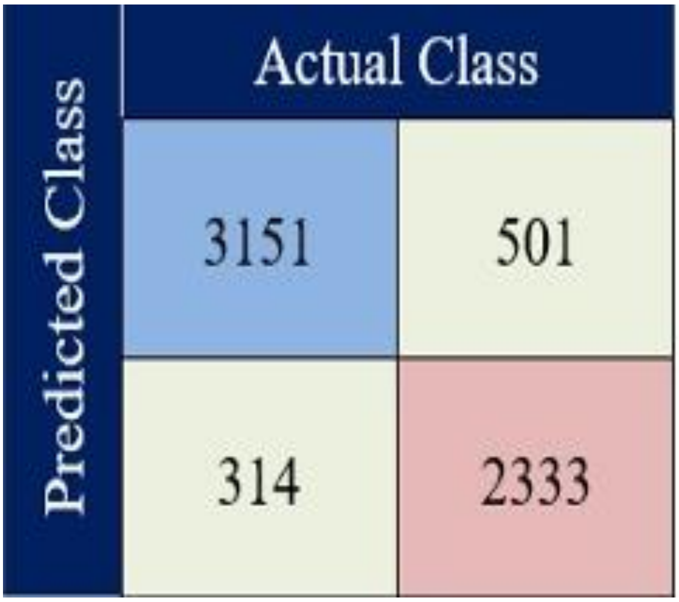

Fig 5 : Shows the confusion matrix of SVM Classifier.

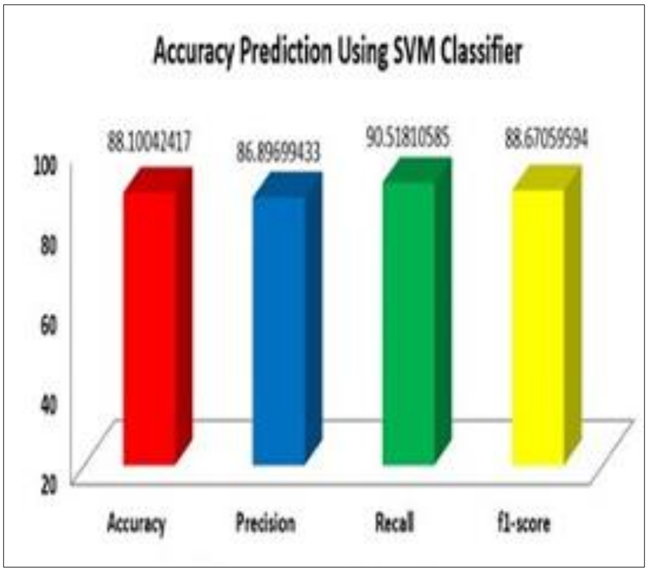

Fig 6 : Shows the Overall Performance of Proposed Classifier

4.2. Decision Tree Diabetic Retinopathy Detection

Diabetic Retinopathy (DR) is a severe microvascular disease of diabetes that can result in permanent blindness if not detected early. Given the increasing prevalence of diabetes globally, there is an urgent need for efficient and automated screening tools to help ophthalmologists in early and accurate diagnosis. Machine learning approaches are increasingly being applied to medical imaging, with the Decision Tree (DT) algorithm being a popular choice given its simplicity, interpretability and success in classification problems. A Decision Tree is a supervised learning algorithm that classifies data by creating a tree-like model of decisions and their possible consequences. For DR detection, retinal fundus images undergo preprocessing to improve their quality by removing noise, normalizing and enhancing contrast. Then, relevant features associated with retinal pathologies, such as microaneurysms, hemorrhages, exudates, and vascular irregularities are extracted via image processing and feature extraction techniques. These features are subsequently used to train the Decision Tree classifier. The algorithm generates a tree structure, in which each node corresponds to a decision made based on a feature, each branch to the various outcomes of the decision, and each leaf node to a class label (e.g., normal or various stages of DR). The tree learns the rules for decision-making from the training data and can accurately classify previously unseen retinal images. Decision Trees are easy to understand and interpret, making them suitable for explaining the decision-making process to medical practitioners. They also have low computational demands and are capable of dealing with both continuous and discrete variables. But they can be susceptible to overfitting, which can be reduced by pruning or ensemble learning approaches. In conclusion, Decision Tree-based methods provide a straightforward yet efficient approach to automate DR detection, leading to early diagnosis and ultimately better patient care. And Figure 7 shows the confusion matrix generated by DT classifier and in figure 8 the overall performance metrics of the DT classifier is shown.

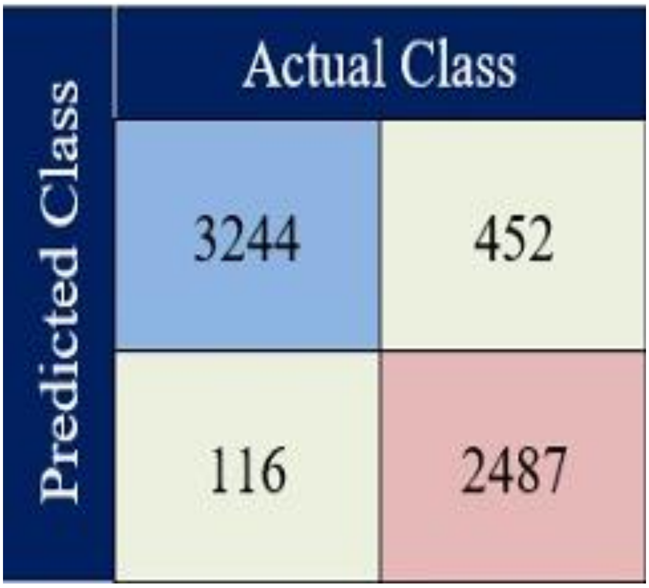

Fig 7 : Shows the confusion matrix of DT Classifier.

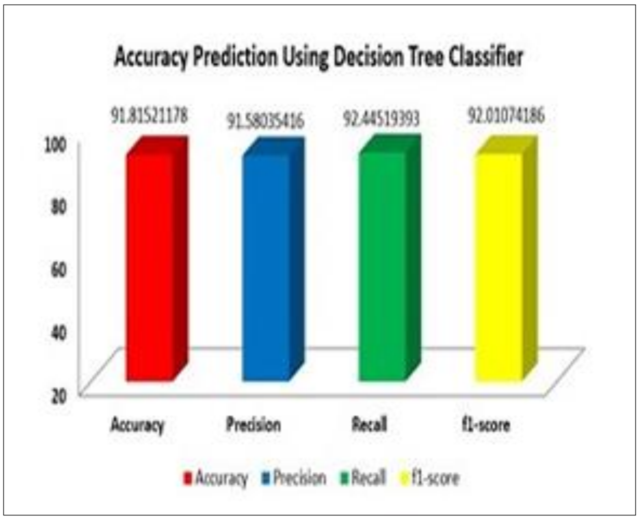

Fig 8 : Shows the Overall Performance of DT Classifier

5. Conclusion

The framework for Diabetic Retinopathy (DR) detection shows significant improvements over traditional machine learning approaches by adopting a combined deep learning architecture of Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN). Here, the CNN is used for discriminative feature extraction from fundus images, while the GAN is used for data augmentation and generation of synthetic images to overcome the lack of data and class imbalances. The proposed CNN+GAN hybrid model attains an accuracy of **96% for the multi-class classification task, substantially better than conventional classifiers such as Support Vector Machine (SVM) with 88% accuracy and Decision Tree (DT) with 91% accuracy. Furthermore, the proposed model exhibits higher precision, recall and F1-score for all five levels of diabetic retinopathy, besides accuracy. In particular, the model shows high recall for the Severe and Proliferative DR classes, which is important in clinical practice to reduce false negatives and ensure early treatment. Additionally, Contrast Limited Adaptive Histogram Equalization (CLAHE) is used in the pre-processing stage to improve image quality and lesion contrast. The GAN-based augmentation is instrumental in enhancing class distribution by synthesizing high-quality retinal images, allowing the model to learn more general and typical features. This ensures similarity in the performance of early and late DR. The hybrid approach demonstrates better generalization, stability and consistency in classification, compared to Phase I models. The diagonal dominance of the confusion matrix suggests that the model classifies with high accuracy and low misclassification between different levels of DR, especially between neighboring classes. Further, the introduction of a Gradio-based web app enhances real-time prediction, making the system more suitable for telemedicine and remote health care. In summary, the CNN+GAN-based approach offers a robust, scalable, and clinically valuable automated solution for diabetic retinopathy detection, which can play a crucial role in early detection and vision loss prevention. Figure 9 shows the overall performance of all 3 classifiers.

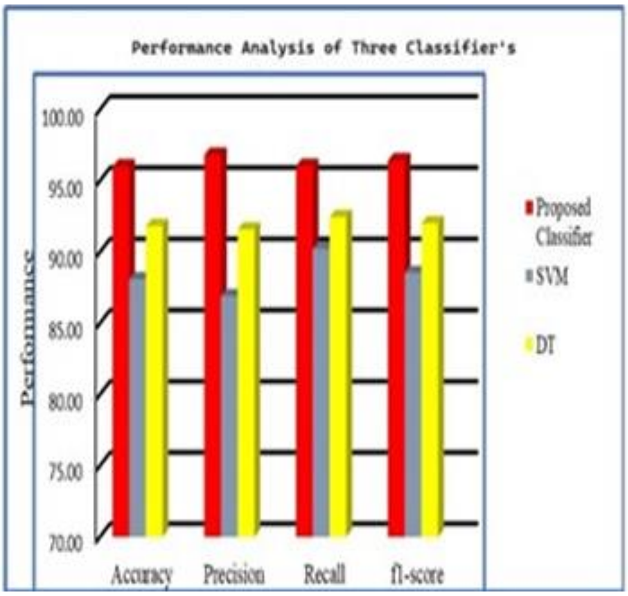

Fig 9: shows the overall performance of all 3 classifiers.

6. Thank-You Note

The author would like to thank previous researchers for their contributions in conducting research on the development of *Virtual Reality* (VR)-based learning media. Thanks to the research results obtained by previous researchers, I and other readers can obtain complete information on the development of *Virtual Reality (VR) -based learning media*. This information will certainly be very useful as a basis for further research to create innovative and useful learning media for students. I hope that the results of writing this article can provide a broader picture of the feasibility and response of students to the *Virtual Reality* (VR)-based learning media that has been developed.

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