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Prediction Of Diabetic Retinopathy Using Weighted Fusion Deep Learning Model

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Abstract *– Diabetes arises from consistently elevated blood glucose levels, which can lead to vascular complications and vision loss. Timely diagnosis signifies a crucial role in minimizing risk of advanced disorder of blood vessels of retina and associated severe visual impairment. Hence, the classification of DR stages holds significant importance. This proposed novel study introduces a weighted fusion deep learning network designed for exigently extracting essential features and characterize DR stages using retinal images. The suggested system intends to iidentify retinopathy symptoms present in these images. Fundus-related features are extracted by fine-tuning the Inception V4 and VGG-19 models. The outputs of these fine-tuned models are combined utilizing a weighted fusion methodology and the ultimate recognition outcome is calculated by using softmax classifier. The suggested network exhibits an elevated degree of accuracy for recognizing DR phases, based on experimental results. The suggested approach specifically obtains an accuracy score of 99.18% and sensitivity of 97.5% when assessed on the Messidor dataset. Our suggested novel weighted fusion deep learning model network has equivalent performance when compared to other models, thus supporting its efficiency.*

Keywords – Diabetic Retinopathy, Inception V4, VGG19, Weighted fusion deep learning model.

1.INTRODUCTION

People with diabetes are susceptible to the chronic eye disorder known as diabetic retinopathy [4]. The blood vessels in the retina, the light-sensitive tissue in the rear of the eye, are impacted. In the initial stages of the disease, symptoms may include blurry vision, difficulty seeing in low light conditions, as well as the presence of spots and floaters. As the disease progresses, It may result in reduced eyesight or possibly total blindness Diabetic retinopathy can be immediately diagnosed and treated to prevent vision loss. Treatment options may include laser therapy, medication injections, or other suitable approaches to address the eye infection. Therefore, early detection and the prevention of vision loss hold great significance for individuals with diabetes. If left untreated, diabetic retinopathy initially may be asymptomatic or result in minor visual impairments, but ultimately, it can lead to blindness [1,12,15].

Retinal Fundus image Analysis [10] examines the intricate patterns and delicate structures within the retina. Each pixel contributes to a vibrant portrayal of ocular well-being, illuminating potential risks such as diabetic retinopathy or DR, glaucoma and Diabetic macular edema . Serving as a vigilant protector, it equips doctors with the knowledge needed to make informed decisions, ensuring timely interventions to preserve vision. A key factor in reducing vision loss is detection of diabetic retinopathy early. Early condition detection permits quick adoption of appropriate interventions and treatments, thereby slowing or preventing the progression of the condition. This proactive strategy guarantees that people with diabetes receive early and appropriate care, lowering the possibility of irreparable retinal damage and maintaining their general visual health.

Additionally, primary healthcare facilities and rural areas in particular lack experts competence in analyzing images of the retina. Consequently, utilizing approaches for computer vision based on deep learning can enhance DR (diabetic retinopathy) detection and broaden the availability of DR screening for patients. Their outstanding performance distinguishes them from alternative models, equipping healthcare professionals with reliable and accurate tools for the quick identification and effective management of DR. Artificial intelligence-based deep learning models have the capacity to learn about crucial data patterns that the human eye might not be able to see. [20].

2. RELATED WORK

In the study conducted by Gulshan et al. [11], Inception V3 was employed to detect diabetic retinopathy (DR) after training it with a dataset consisting of 128,000 fundus images. Impressive accuracy rates of 99.1% and 97.5% were shown by the results. The HPTI-v4 diagnostic model for the classification of diabetic retinopathy (DR) was published by Shankar et al. [3], with astounding levels of accuracy (99.49%), specificity (99.68%), and sensitivity (98.83%).Using the Messidor dataset, Shanthi et al. [13] structurally altered the AlexNet framework and attained a typical accuracy score of 96.25%. In Reference [14], the authors proposed a method for classifying healthy and diabetic retinopathy (DR) cases through the merging of pre-processed images with weights. This method combined the use of a decision tree algorithm and a residual network. The authors said that their sensitivity was 93%, an AUC (Area Under the Curve) of 94%, and a specificity of 87%. Furthermore, in a study mentioned in Reference [19] and utilizing the Messidor dataset, a proposed approach For the purpose of classifying fundus images, Inception-ResNet-V2 with the Moth optimization strategy is used. The stated results showed a 99.12% accuracy rate and a 97.91% sensitivity .

Attia et. al. [6] conducted a survey that explored classification methods for diabetic retinopathy (DR), which has a primary focus on deep learning strategies and a secondary concentrate on traditional methods. Alyoubi et al. [7] reviewed 33 studies that used deep learning for classification in their review. They stressed the value of ongoing deep learning model improvements, particularly in view of the increased prevalence of Diabetes.

3. METHODOLOGY

3.1 Dataset Description

Presented in Table 1 is the Messidor dataset. The Messidor database consists of 1,200 eye fundus color quantitative images of the rear pole. These diabetic individuals' retinal pictures were gathered by three distinct ophthalmologic departments. The Messidor database's standardized and digitalized eye fundus photographs are a useful tool for the study and advancement of diabetic retinopathy.

Table1. Messidor Dataset Description

Stages of DR	Feature Details	Number of Images	Label
Healthy	Zero Abnormalities	548	Normal
Mild DR	Microaneurysms	152	Stage 1
Moderate DR	Few MA		
		246	Stage2
Severe DR	Venorous beading + Intraretinal microvascular abnormality		
Proliferative DR	Vitreous/Pre-retinal hemorrhage	254	Stage 3

3.2 Transfer Learning

Capacity to pass on knowledge and ideas from one closely related domain to another is transfer learning [10]. Transfer learning enables the application of previously acquired knowledge and representations from one task to enhance the efficiency of another associated task. Transfer learning strengthens deep learning models by employing pre-trained networks which have identified complex patterns across large datasets to quickly adapt and generalize to new problems, even with limited labeled data. With this method, there is no requirement for starting from beginning and both low-level traits and high-level concepts may be transferred, which reduces the amount of time and resources needed for training.Fig.1. represents Block diagram of proposed model.

3.3 Block diagram

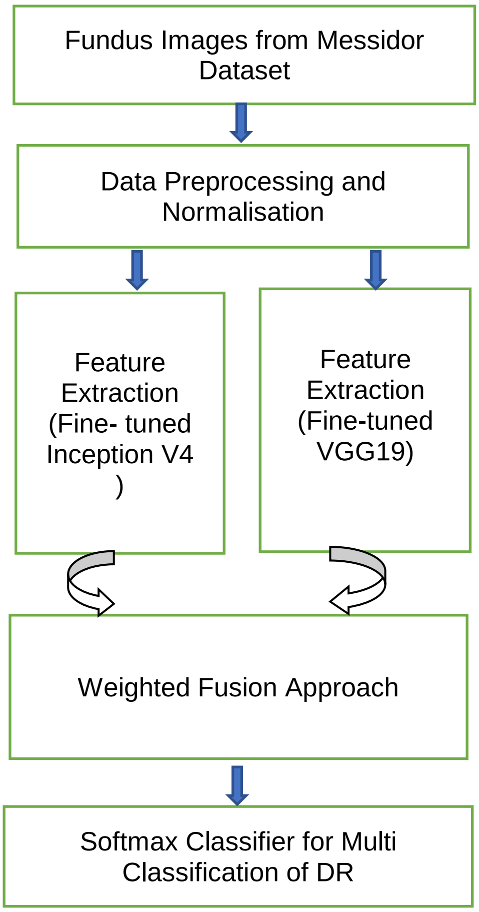

Fig. 1. Block diagram of the proposed model

3.4 Feature Extraction:

In this article, two CNN architectures, namely VGG-19 and Inception V4, were employed. By utilizing VGG-19 and Inception V4 as feature extractors, the model benefitted from their learned representations while customizing the remaining layers for the specific problem being addressed.Fig.2,4,6 represents Confusion matrix of pretrained deep learning models.Fig.3,5,7 represents ROC-AUC Curve of pretrained deep learning models .

3.5 Weighted Fusion Deep learning Model*:*

Deep learning's introduction has revolutionized a number of fields, including computer vision and medical imaging. The weighted fusion deep learning approach is one of the outstanding methods that has attracted a lot of interest by using varying weights to fuse several sources of data or characteristics.. The process of weighted fusion entails merging findings or features obtained from several models or techniques in a weighted manner. Instead of relying solely on a single model or approach, the weighted fusion deep learning model capitalizes on the diverse information captured by each individual model. The fusion process assigns weights to the outputs of each model, prioritizing the more informative and reliable predictions while mitigating the potential limitations of individual models. In this model, the neural network receives features from many sources as input and computes their weighted sum. Each feature source's associated weights are discovered throughout the training process. This enables the model to automatically assign more weight to sources that are authoritative or informative while giving less weight to sources that are less relevant. This approach enhances the overall predictive capability and leads to more robust and accurate outcomes.

4. EXPERIMENTS AND RESULTS

We used a number of metrics as evaluation criteria to determine how well our suggested Weighted Fusion Network performed diagnostically. These measurements include accuracy (ACC),Recall, precision (PRE),F1score. Equations (1) to (4) offer the corresponding numerical expressions for each metric.

The accuracy (ACC) formula is:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \qquad (1).$$

Calculating recall (R) is as follows:

$$\text{Recall} = TP / (TP + FN) \qquad (2).$$

Precision (PRE) is determined as follows:

$$\text{Precision} = TP / (TP + FP) \qquad (3).$$

The harmonic mean of precision and recall (or sensitivity) is used to generate the F1-score:

$$\text{F1-score is calculated as follows} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \qquad (4)$$

In this case, TN stands for true negatives, TP for true positives, FP for false positives, and FN for false negatives.

Fig.8,9,10 represents Classification result of pretrained Deeplearning models on Messidor Dataset. These performance metrics are very useful for classification of diabetic retinopathy . Deep learning classification model effectiveness is assessed using performance indicators. These metrics provide insight into how well a model is doing in terms of accurate data classification.

Results:

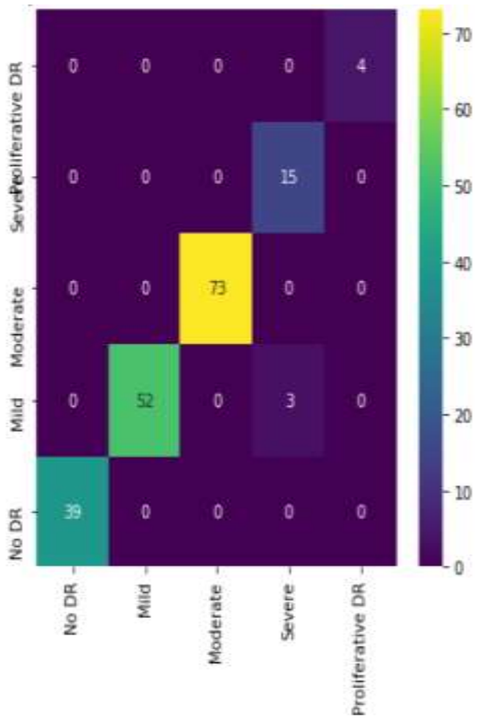

Fig. 2. Confusion Matrix of Inceptionv4 trained on Messidor dataset

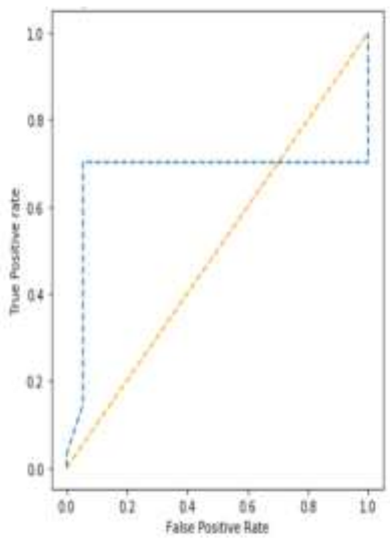

Fig. 3.ROC AUC Curve of Inceptionv4 trained on Messidor dataset

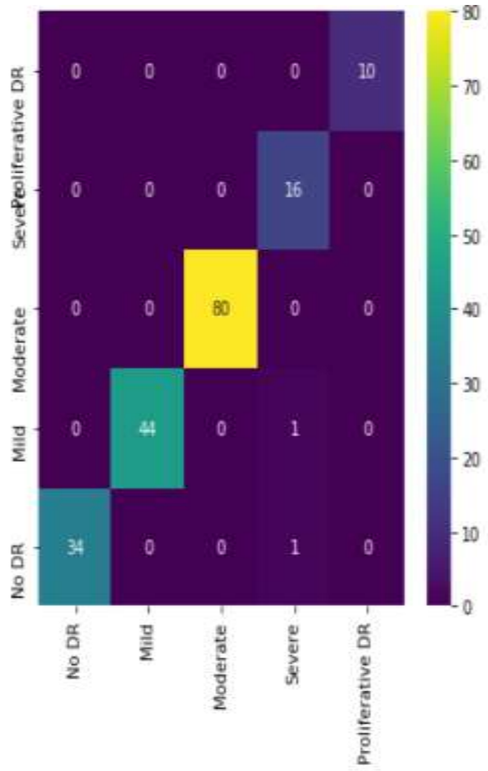

Fig. 4. Confusion Matrix of VGG19 trained on Messidor dataset

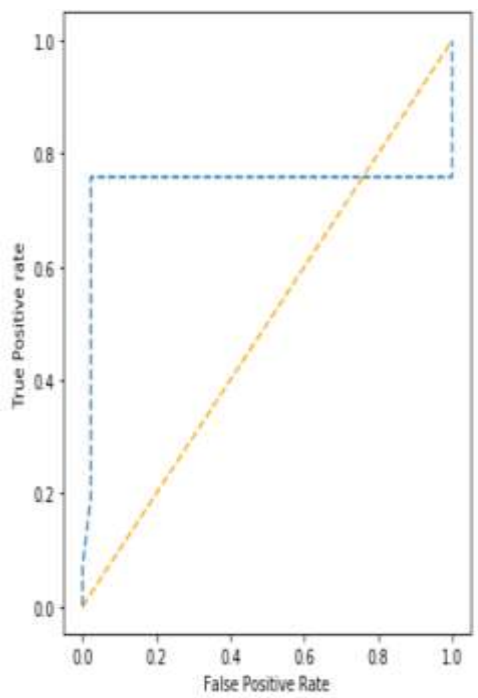

Fig. 5.ROC AUC Curve of VGG19 trained on Messidor dataset

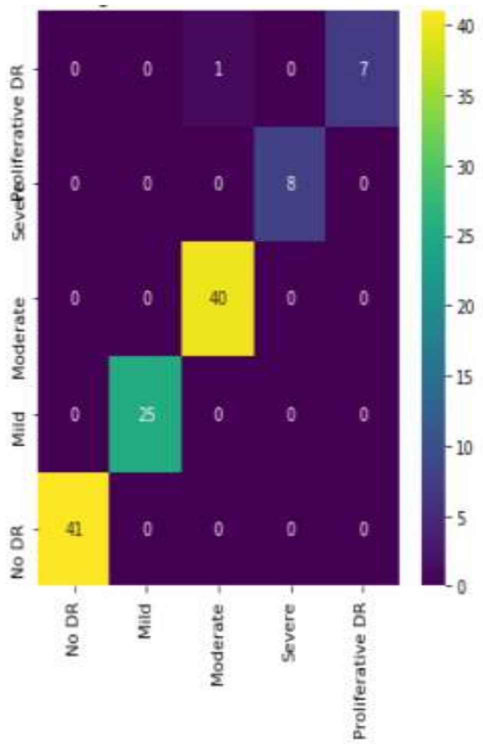

Fig. 6. Confusion Matrix of Weighted fusion of Inception V4 and VGG19 TRAINED ON Messidor dataset

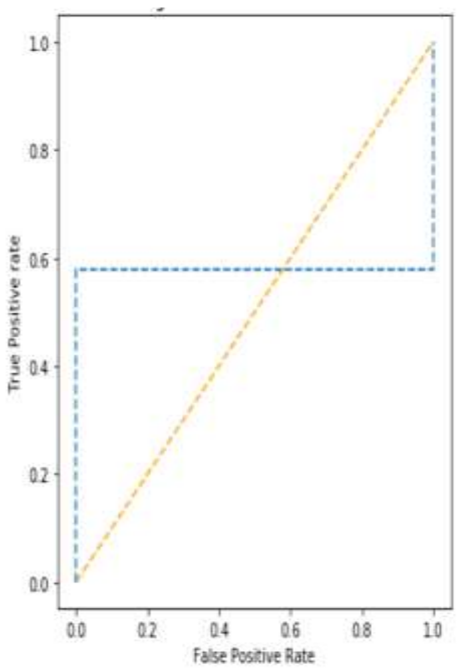

Fig. 7.ROC AUC Curve of Weighted fusion of Inception V4 and VGG19

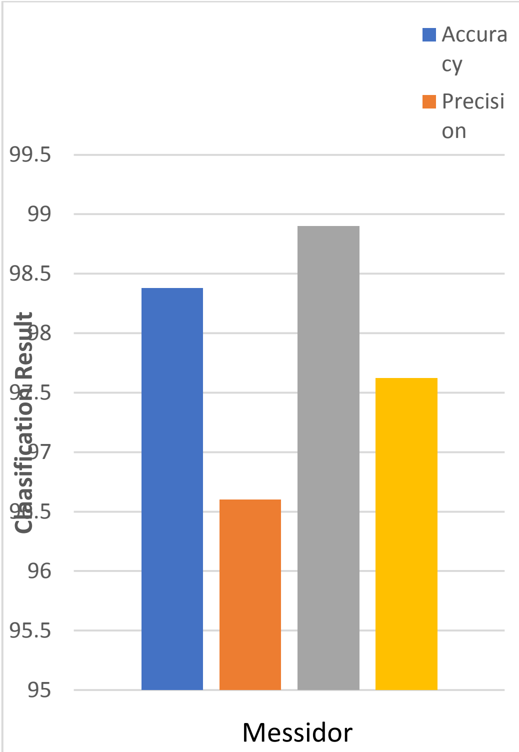

Fig. 8. Inception V4 Classification Result on Messidor Dataset

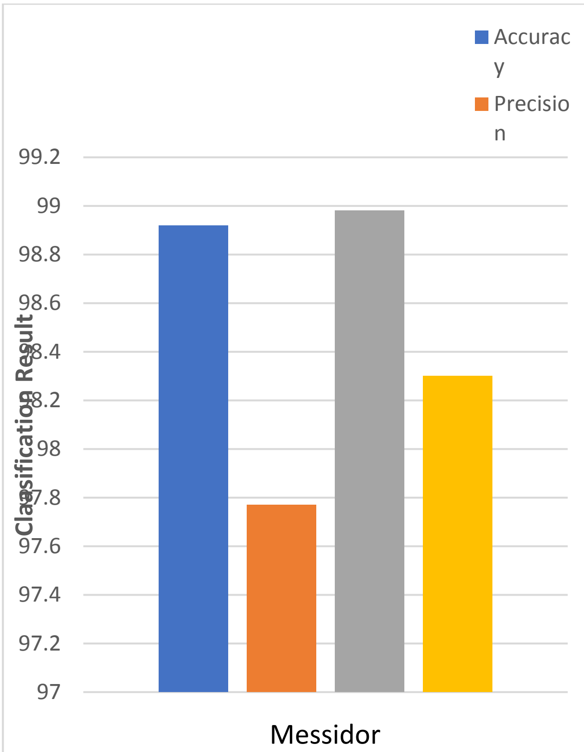

Fig.9.VGG19 Classification Result on Messidor Dataset.

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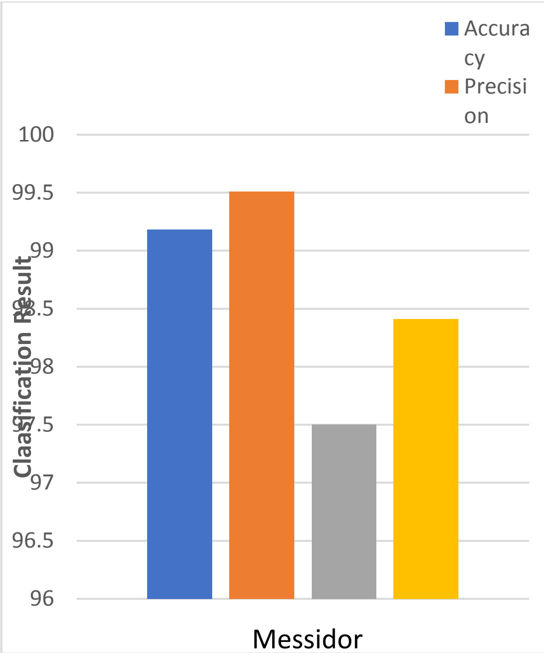

Fig.10 Weighted Fusion Classification Result on Messidor Dataset

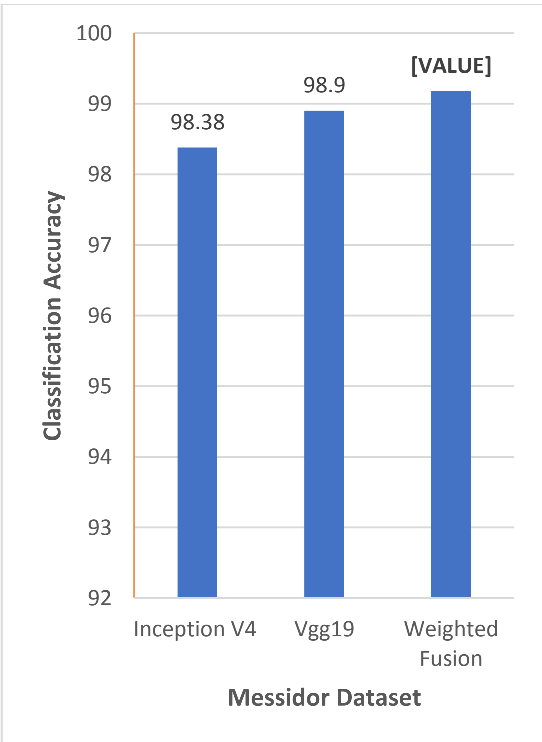

Fig.11 Comparision of Accuracy of Inception V4 , VGG19 and Weighted fusion on Messidor Dataset.

4.1 Comparision :

Our proposed method was compared to several contemporary methods[16] using Messidor Dataset. As shown in Table 4, our model achieved the highest Accuracy of 99.18%. The techniques of Wang et al. [17] and Chen et al.[18] were closely behind both achieving a score of 99.1% and 99.2% on the Messidor dataset.Fig.11.represents Comparision of pretrained deeplearning models.

Table2. Result comparision of our proposed model on Fundus Classification Messidor dataset .EEL-End to end learning.

Model	Type of Training	Technique	Process Type	ACC	Recall
Wang et al.[17]	Zoom	EEL	Fundus Classification	91.1	-
Chen et al.[18]	SI2DRNet	EEL	Fundus Classification	91.2	87.0
Gulshan et al.[11]	CNN	Transfer Learning	Fundus Classification	-	87.0
Grace Ugochi Nneji et al.[16]	CNN	Transfer Learning	Fundus Classification	98.5	98.9
WFDLN[Proposed]	**CNN**	**Transfer Learning**	**Fundus Classification**	**99.18**	**97.5**

5. CONCLUSION

Our article presents a novel approach for identifying diabetic retinopathy (DR) using a weighted fusion deep learning methodology. The VGG-19 and Inception V4 models were fine-tuned to extract relevant features from fundus images related to diabetic retinopathy. These features were merged using a weighted fusion strategy to leverage the complementary information provided by each model. By utilizing a softmax classifier, we obtained fused features. A comparative analysis with existing techniques revealed that our The suggested design outperforms a number of cutting-edge models in terms of performance. With an accuracy of 99.18%, precision of 99.5%, recall of 97.5%, and an F1 score of 98.4%, the evaluation findings on the Messidor dataset demonstrate exceptional performance. The obtained results confirm that our proposed weighted fusion model achieves cutting-edge accuracy in identifying diabetic retinopathy (DR). This model offers a robust and efficient solution, providing invaluable support to ophthalmologists and streamlining the diagnostic process, ultimately saving valuable time.

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