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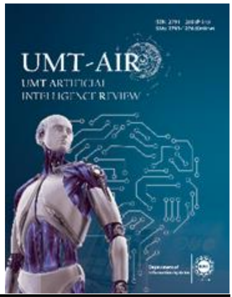

Title: **Deep Learning Model Training and Evaluation Framework for Diabetic Retinopathy Detection Using PSO-Optimized Hyper Parameters**

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Deep Learning Model Training and Evaluation Framework for Diabetic Retinopathy Detection Using PSO-Optimized Hyper Parameters

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ABSTRACT Currently, numerous healthcare physicians are having hitches detecting diabetic retinopathy early in patients. This disease's primary warning indications are challenging to detect. A clear-cut instruction technique is compulsory to detect this condition timely. Deep learning is one method to use for this purpose. This work used a particle swarm optimization (PSO) technique to select the optimal Diabetic Retinopathy. Applying deep learning with particle swarm optimization (PSO) resulted in a 73.11% increase in outcome. This VGG19 model exhibits training and validation losses of 0.755 and 0.7151, respectively. VGG19 shows the finest simplification capability, as realized since the minor variance among training and validation victims. This model realizes steadily on together training and hidden data.

INDEX TERMS Diabetic Retinopathy, Deep learning, Classification, VGG19, Particle Swarm Optimization (PSO), Inception v3, MobileNetV3

I. INTRODUCTION

Diabetes is a sickness that affects 463 million persons aged 20 to 79. Diabetes is among the the ten most common reasons of death among deceased individuals these days. In this illness, the pancreas is incapable to produce sufficient insulin hormone or is unable to use the insulin hormone sufficiently, consequentially raising blood sugar levels in the body. Analyzing World Health Organization's (WHO) estimations, one uncovers that diabetes destroyed 1.6 million persons in 2015 [1], with Indonesia having the highest percentage of this disease in the Asia-Pacific. High plasma sugar stages are a significant feature of this chronic, incurable condition triggered by insulin manufacturing problems. Type 2 diabetes, also identified as non-insulin-dependent diabetes mellitus, is extremely common in various countries and frequently affects persons aged 30 to 60. This disease is mostly caused by an unnatural lifestyle [2].

Diabetes can take a severe toll on a person's life if not diagnosed and treated early. Examples contain pancreatic harm, outlying vascular illness, cardiovascular failure, renal failure, blindness, and weight damage [3]. Diabetes retinopathy remains as the lone diabetes that was exposed to be the cause of blindness. Insulin levels in the blood rise, fetching the root of diabetic retinopathy, a chronic disease that needs crucial treatment to avoid blindness. The patient's primary diabetic retinopathy spine not directly root blindness [4]. Medicinal professionals and technical studies normally decide that premature diagnosis raises the chances of recovery [5]. In view of this, early detection of diabetic retinopathy is critical for depressing the

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risk of blindness. Several specialists have conducted studies to detect diabetic retinopathy at its primary stage.

II. LITERATURE REVIEW

To contextualize our research study, we examined a variety of articles on topics such as diabetic retinopathy, deep learning algorithms, machine learning techniques, image processing, illness forecasts, and further. In 2014, B. A. Hajdu and Antal did a remarkable study that assisted us greatly. This work intensive on the messidor dataset and employed machine learning classifiers to reach ensemble learning [6]. Applying different algorithmic approaches, such as neural networks, fuzzy C-means, and multilayer preceptor [7], other researchers, notably Herliana in 2016, reduced the procedure by implementing the Correlation-based Elements Determination (CFS) [8]. Research from 2016 suggested excellent precision in categorizing Pap Smear individual cells, emphasizing the significance of feature selection in boosting model performance [9]. Diabetic retinopathy was a serious complication of diabetes that must be identified and addressed early to prevent loss of vision [10].

Author proposed the study asserts that a fully associated network can be efficiently applied for noticing diabetic retinopathy, to get hopeful results for initial diagnosis, assisting in better recognition of the disease [11].

Author proposed PSO demonstrates to remain an active tool for feature range in retinal image organization, smoothing better presentation and abridged resource feasting in diabetic retinopathy detection [12].

An author proposed in their study that MobileNet delivers a lightweight, however, actual solution for correctly classifying skin injuries, making it apposite for mobile and resource-constrained strategies [13].

Another paper proposes the practice of MobileNet for finding apple leaf ailments. The study achieves that MobileNet proposes a highly effective and precise solution for noticing numerous apple leaf ailments, making it appropriately aimed at mobile applications and actual agricultural disease checking [14]. An author proposed in their paper, a technique for detecting potato leaf ailments with the Inception V3 NN model. The study achieves that Inception V3 efficiently identifies numerous potato leaf diseases by high accuracy, presenting a reliable key for farming disease supervision [15].

III. RESEARCH METHODOLOGY

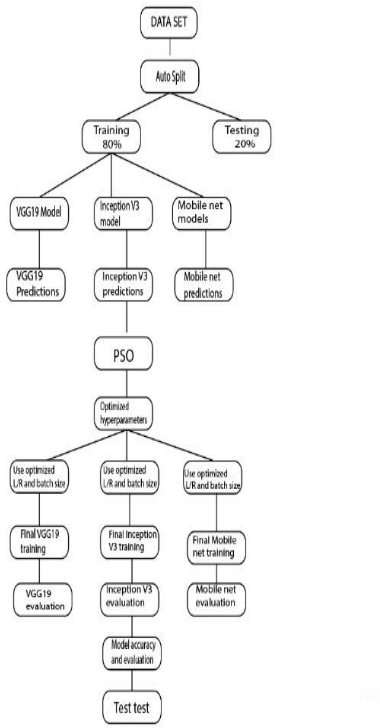

FIGURE 1. Diagram of phases in our model

A. DATASET DETAIL AND SPLIT OPTION

The dataset composes of images from five unique classes: “Mild, No_DR , Moderate, Serve and Proliferate_Dr”. these images were customized t0 128x128 pixels. The dataset was spontaneously divided into testing (20%) and training (80%) set to assess model efficiency. The dataset comprised of images from five unique classes: “Mild, No_DR, Moderate, Serve and Proliferate_Dr”. These images were customized t0 128x128 pixels. The dataset was spontaneously divided into testing (20%) and training (80%) set to assess the model efficiency.

B. DEEP LEARNING MODELS

There are three unique deep learning models that were chosen for extraction and grouping. VGG19: a model that was previously trained using the ImageNet dataset. The data defrosted for 10 years to be approved for improvement. InceptionV3: it was another pre-trained model extracted by the image net dataset. There were last five unique layer were defrosted enhancement. Mobile Net: they were non-essential model under processes for last 10 year defrosted for improvement. Each subsequent model was trained by adapted construction where spatial global aggregation layer and entirely linked subsequent layer were included to process dimension reduction through a unique softmax yield level for categorizing five unique classes. After learning, the models produced output forecasts, representing the categorization of diabetic retinopathy pictures into one of five categories. To improve the accuracy of classification, the Particle Swarm Optimization (PSO) technique was applied to tune each model's parametric variables. PSO was utilized to optimize every model's hyper parameters, namely the learning rate and batch size. The swarm found the optimal combination of these features to maximize accuracy in validation and therefore improve model performance.

C. PSO

Using particle swarm optimization, I identified the batch size and learning rate, and we then fitted three models MobileNet, VGG19 and InceptionV3 and the accuracy were obtained.

PSO modified these parameters, leading to enhanced efficiency throughout all three models. Following the optimisation procedure, the resulting models were checked for correctness on the test data. Performance indicators like accuracy, recall, and F1 score for each class were calculated to determine how successfully the models generalized to previously encountered data.

IV. RESULT

TABLE I
INCEPTION V3

Class	No_DR	Mild	Moderate	Severe	Proliferate_DR
Precision	91%	29%	49%	17%	19%
Recall	77%	47%	48%	28%	14%
F1 Score	83%	36%	48%	21%	16%

The table 1 demonstrates the Inception v3 model's ability to categorize different phases of diabetic retinopathy (DR). The framework works well in the No_DR class, with a F1 rating of 83% and high accuracy (91%). But it falls greatly during the phases of Moderate, Mild, Severe, and Proliferative_DR stages, when recall, accuracy, and F1 scores are significantly lower, particularly for Severe and Proliferative_DR (precisions reaching as low as 17% and 19%, respectively). These data indicate that, while the model is great at recognizing healthy individuals, it fails to distinguish between the extra severe and serious stages of DR, possibly due to overlying features or class disparity.

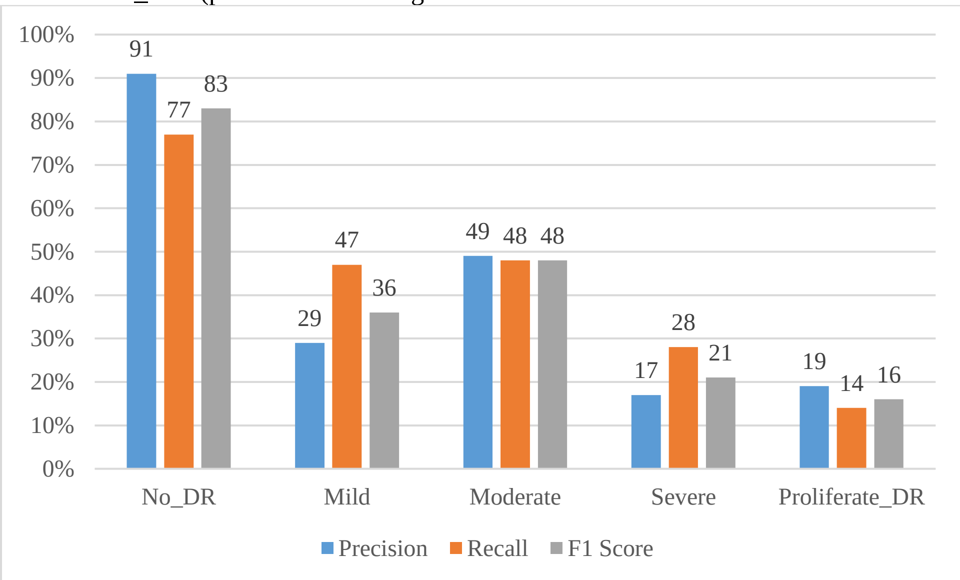

FIGURE 2. Inception v3

TABLE II
MOBILENETV3

Class	No_DR	Mild	Moderate	Severe	Proliferate_DR
Precision	98%	61%	48%	36%	52%
Recall	79%	12%	91%	48%	31%
F1 Score	87%	21%	63%	41%	38%

The above table 2 is meant for MobileNetV3 in categorizing Diabetic Retinopathy (DR). It displays robust performance designed for the No_DR class, by great precision (98%) and a decent F1 score (87%), representative of consistent identification of well cases. In this Moderate DR class, the simulation has a high recall (91%), but an equal F1 rating of 63%, implies medium accuracy. But efficiency suffers in the Proliferate_DR, Mild, and Severe phases, when F1 scores were short (38%, 21%, and 41%, respectively), showing difficulties with recognizing those phases, notably Mild DR, that has a particularly poor recall (12%). It demonstrates that the technique struggles to recognize the initial stages and severe DR.

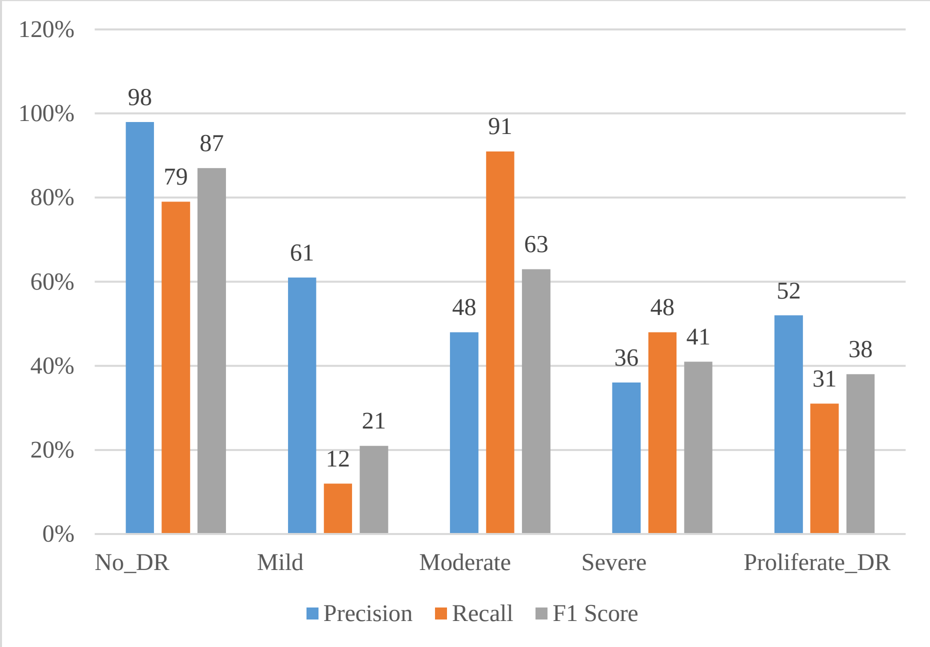

FIGURE 3. Mobile net v3

TABLE III
VGG-19

Class	No_DR	Mild	Moderate	Severe	Proliferate_DR
Precision	94%	59%	62%	39%	33%
Recall	97%	47%	68%	45%	25%
F1 Score	96%	52%	65%	42%	29%

In the above table 3, VGG-19 model No_DR class performs outstandingly in detecting cases deprived of diabetic retinopathy, by great precision (94%), and F1 score (96%) and recall (97%). It is actually consistent at classifying healthy cases. Mild DR class: The model fails at classifying mild cases of DR, showing modest low recall (47%), precision (59%) subsequently, a low F1 score (52%). It frequently misses mild cases, representative of difficulty in distinctive early-stage DR. Moderate DR class VGG-19 shows uncertain display in detecting moderate DR, with precision (62%), recall (68%) and a F1 mark of 65%**.** It achieves relatively fine results but can be improved. Severe DR class: The model underachieves in noticing severe DR, with short precision (39%) and recall (45%), leading to a F1 score of 42%. It fights to distinguish severe cases from other phases. Proliferative DR class: The model achieves unwell results in classifying proliferative DR, with **s**quat precision (33%) and very stumpy recall (25%), ensuing in a F1 score of 29%. It frequently misclassifies these cases.

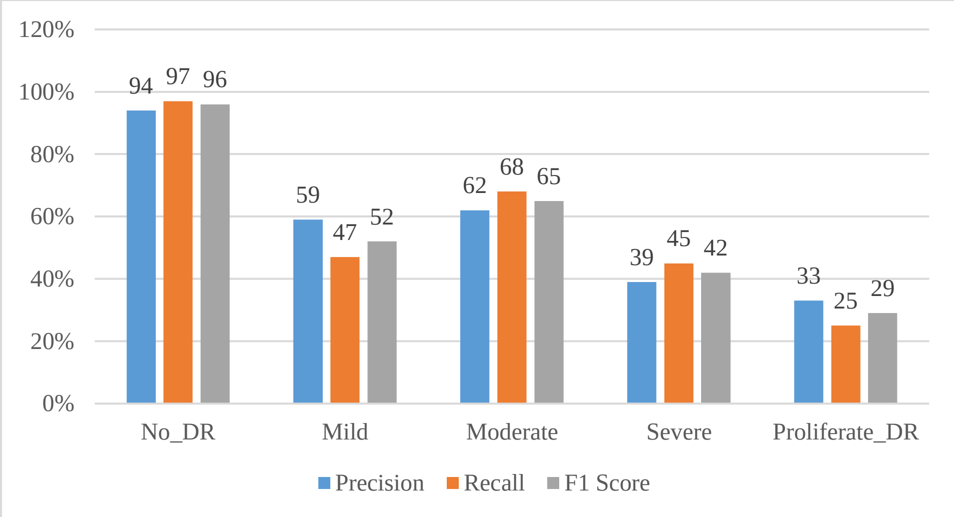

FIGURE 4. VGG-19

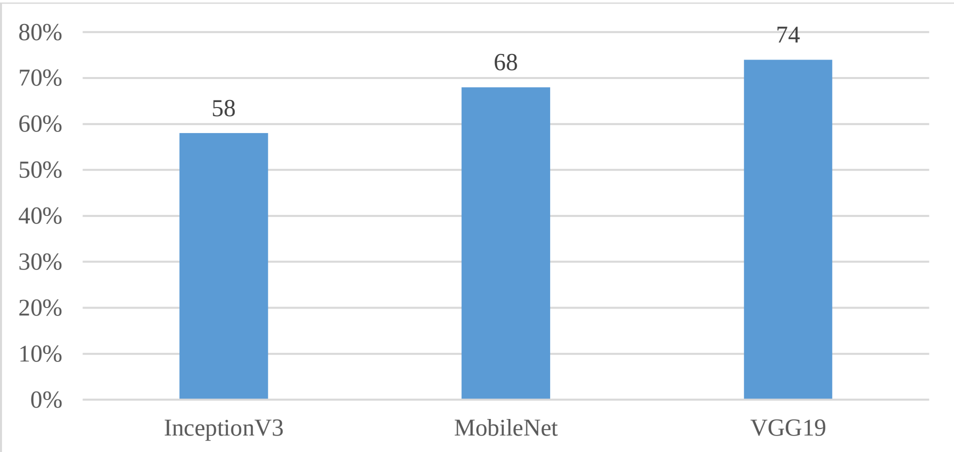

FIGURE 5. Accuracy

TABLE IV
ACCURACY

	InceptionV3	MobileNet	VGG 19
Accuracy	58%	68%	74%

The combined accuracy of three distinct models VGG19 (74%), MobileNet (68%) and InceptionV3 (58%) shows that VGG19 outdoes the other models in categorizing diabetic retinopathy phases, reaching the uppermost accuracy. MobileNet demonstrations moderate, while InceptionV3 has the lowermost accuracy, signifying its inability to correctly classify the stages of diabetic retinopathy. VGG19's higher accuracy imitates its more reliable act across the numerous DR classes, while InceptionV3 can need more refinement or data balancing to recover classification accuracy.

V. CONCLUSION & FUTURE WORKS

VGG-19 provides outstanding results for diagnosing diabetic retinopathy, with the most accuracy (74%), and strong outcomes across all severity levels. MobileNetV3 succeeds in No_DR precision (98%) but struggles with severe instances, whereas Inception v3 shows strong initial detection (f1 score 83% for No_DR) but comes behind in later phases such as Proliferate_DR (f1 score 16%). More enhancements must be made for severe DR diagnosis.

As a result of addressing these future research guidelines, we purpose to improve and enlarge the applicability of the LSTM-PSO model for Diabetic Retinopathy classification, causal to developments in medical imaging and deep learning procedures collectively.

CONFLICT OF INTEREST

The author of the manuscript has no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

DATA AVAILABILITY STATEMENT

Data will be provided by corresponding author upon reasonable request.

FUNDING DETAILS

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