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Diabetic Retinopathy Detection Using VGG-16 Deep Learning Architecture

Abstract: - In the human body, the light-sensitive tissue is the retina, which is located at the back of the eye. In recent years, the impact of diabetes on the retina has gradually increased with a disease called diabetic retinopathy (DR), an ocular disorder. The long-lasting high level of sugar proves that diabetic patients may damage the retina's small blood vessels; this results in illness and blindness if it is not detected in the early stages. Reducing the risk factor of vision loss is possible with prompt detection and therapy of DR. Recent developments in healthcare systems adopting machine learning (ML) and deep learning (DL) models have gained a lot of popularity for image processing and analysis, early detection, and predictions with available data in a variety of applications. The performance of DL models on unbalanced data results is less accurate because most datasets related to DR are unbalanced to train the deep learning model. To overcome this problem, proposed the Pre-**Synthetic minority oversampling technique** (Pre-SMOTE) approach to converting unbalanced data into balanced data. And we used the **visual geometry group -16 (**VGG-16) model to evaluate the proposed approach. The experimental results demonstrate that the suggested model performs better in terms of accuracy (79.99%) when compared to state-of-the-art methods**.**

Keywords: Diabetic Retinopathy, Deep Learning, Machine learning, Synthetic minority oversampling technique (SMOTE), visual geometry group -16 Architecture (VGG-16)

I. INTRODUCTION

Retinopathy disorder affects the retina of the eye and is caused by different diseases like diabetes, hypertension, persistent kidney sickness, and coronary illness [1]**. The two primary phases of diabetic retinopathy (DR), Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). NPDR is a benign variant of the illness that causes early retinal swelling [1,18,24]. The last stage of the disease PDR is marked by the development of new blood vessels on the retina's surface. Because of their fragility and propensity to leak into the vitreous, these veins may cause visual impairments.** If it fails to be identified in time, it may cause in blindness [23]. Diabetic Patients frequently face this issue, which causes permanent eyesight loss that cannot be fixed once it has occurred. Early identification of DR can prevent the above-mentioned issues of DR. In addition to that minor symptoms of DR are challenging situation to recognize DR in patients at very beginning stage. To overcome the early identifications of DR and minor symptoms of DR, Ophthalmologists [21] and specialists are more adopting AI-based equipment's [2]. DR has various grades of severity levels, which are 0, 1, 2, 3, 4.

0- No_DR: The lack of any harm, illness, or severity. No serious concerns or difficulties have been found.

1- Mild: It is considered to be minor; this level usually indicates the existence of an issue or harm. It might allude to a little effect or harm.

2- Moderate: This category denotes a moderate level of illness, disease, or severity. Compared to "Mild," the impact is greater but still not as great as "Severe."

3- Severe: A high degree of illness, damage, or severity is indicated by this level. The impact is significant, and the problem might need to be treated with immediate attention or action.

4- Proliferate_DR (Proliferate Damage or Disease): This category suggests that the illness or damage is not only expanding or multiplying but also becoming more serious. It implies that he severeness of the problem has suddenly or noticeably escalated [3].

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Each phase has distinct qualities and traits of its own. Consequently, the concept of developing an automated method for DR arises. The possibility of revolutionary change of AI and ML is improved the diagnosis of diabetic retinopathy through early detection, efficiency for large volume of medical images, enhanced the reliability of diagnoses. In context of DR Most of the investigation was conducted using machine learning techniques for feature extraction; DL has emerged as a popular method that performs better in DR fields, including the analysis and categorization of medical images [4]. But deep learning has become more and more popular recently in a number of domains, including sentiment analysis, handwriting identification, stock market forecasting, and medical picture analysis, among others. CNN tends to yield useful outcomes in deep learning tasks involving picture categorization such as deep convolutional neural networks information fusion and improved whale optimization algorithm based smart oral squamous cell carcinoma classification framework [28]; Brain Tumor Classification from MRI Scans: A Framework of Hybrid Deep Learning Model with Bayesian Optimization and Quantum Theory based Marine Predator Algorithm [29]; Deep Convolutional Neural Networks for Accurate Classification of Gastrointestinal Tract Syndromes [30]. The VGG-16 CNN was used to detect diabetic retinopathy. Because of their superior performance in image recognition tasks, CNN are particularly well-suited for medical image analysis [5,20]. VGG-16 provides a robust basis for recognizing pathological irregularities connected to diabetic retinopathy and extracting complicated properties from retinal images due to its deep architecture and demonstrated effectiveness in a variety of image classification tasks [6]. Most of the existing research has done on balanced and unbalanced data. When compared to the balanced data, Unbalanced data trained model classification is less accurate. To overcome classification issue on unbalanced data to get efficient results proposed pre-Smote approach to train the model for classification [7].

II. METHOD

The main objective of the proposed model to maintain the unbalanced data to balanced using smote algorithm and trained the vgg-16 model. To identify diabetic retinopathy depending on severity level (No DR, Mild, Moderate, Severe, and Proliferative DR), this study uses the deep learning technology. Figure 1 depicts the process flow diagram for the DR Detection Model. Based on the DR flow diagram the Data is initially gathered, image preprocessing is carried out, and data augmentation is performed using the pre-smote approach to balance the data. Further, the vgg-16 model has been validated and trained. The outcomes are displayed.

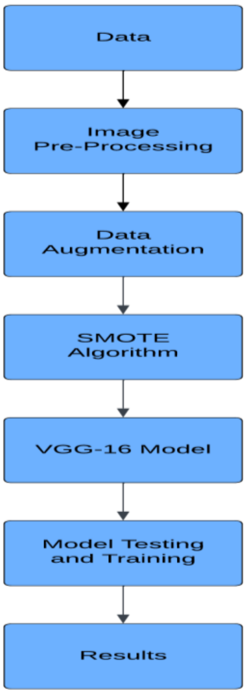

Fig. 1 Flow Diagram of DR

2.1 Image Pre-Processing

The dataset's images [8] are cropped to a standard size of 224 x 224. 20% were designated as validation sets and the remaining 80% as training sets. The train dataset consists of 2931 images, and the validation set has 731 images of 5 classes. Using the Keras Image Data Generator, image augmentation is carried out with the following parameters: The re-scale is set to 1/225, shear, zoom, and ranges for width and height shifts are set to 0.2, and horizontal flip is provided as true [19, 27].

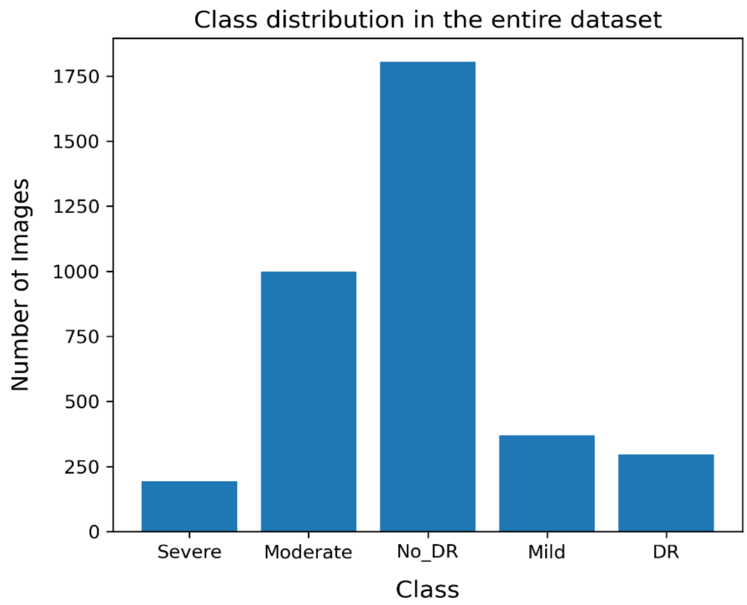

Fig. 2 Class distribution of the Entire Dataset

There are 2931 images in all in the data set. Each image corresponds to a certain diabetic retinopathy (DR) severity level. The following represents the distribution of images among the DR severity categories:

- No DR: 236 images
- Mild DR: 296 images
- Moderate DR: 800 images
- Severe DR: 1444 images
- Proliferative DR: 155 images

indicates a possibly unbalanced dataset by showing that the bulk of the images fall into the "Severe DR" category, which gives insight into the class distribution within the training dataset [9].

2.2 Data Augmentation

From the above Figure 2, the image classes are imbalanced. The minority groups are Severe, Moderate, Mild, and DR, whereas the majority class is No_DR. whereby instances are distributed differently throughout the classes. When identifying the diabetic retinopathy minority class, the model may exhibit a bias towards the majority class. As such, there's a possibility that the model will be less.

Pre-SMOTE Algorithm:

Input: unbalance image data

Output: balanced image data

1. Locate Instances of Minority Classes, which has fewer instances than the majority class, is the class to which SMOTE is normally applied X, Y.
2. Choose a minority instance at random from the minority class.
3. For the chosen instance, find the nearest neighbors (k). This is a user-defined parameter.
4. Determine the distance in Euclid between the chosen example and every other instance in the minority class.
5. Find the k instances that represent the closest neighbors and have the smallest distances.
6. Create Artificial Samples and Reproduce X_resampled, Y_resampled.

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accurate in identifying severe cases of DR. The most prevalent oversampling method [10] for resolving imbalance problems is SMOTE (synthetic minority oversampling technique). By duplicating minority class cases at random, it seeks to achieve class distribution parity. SMOTE creates new minority cases by combining preexisting ones. For the minority class, it uses linear interpolation to create virtual training records. For every example in the minority class, k-nearest neighbors are arbitrarily chosen to create these synthetic training records. The image data is reconstructed following the oversampling procedure, and several classification models can be employed in the data processing.

From Pre-SMOTE algorithm, Important libraries are scikit-learn for creating datasets (make-classification), pandas for data processing, matplotlib for charting, NumPy for numerical operations, and imbalanced-learn (imb_learn) for SMOTE. Imported are the libraries needed for the SMOTE model. Using scikit-learn's make_classification, a synthetic dataset is created. 4289 samples, 5 features, and 5 informative features make up the dataset. The distances between the five classes, each with three clusters, are 0.8. To oversample the minority classes in the dataset, SMOTE is used. The nearest neighbors [11] that will be utilized to create synthetic samples is determined by the k-neighbors option(k=2). Repeatability is ensured by setting the random state. The resampled data is saved in X_resampled and y_resampled after applying SMOTE. Figure-3 is produced to show the distribution of the classes. The classes are shown on the x-axis, while the instances is shown on the y-axis. After the SMOTE is applied X_resampled is 4310 and Y_resampled is 4310. The dataset is balanced [12]. The balanced test dataset has 862 pictures, whereas the balanced train dataset contains 3448 images.

2.3 VGG-16 Model

The acronym "VGG-16" refers for "Visual Geometry Group 16-layer," indicating the network's depth. It is unique in that it consists of only 16 layers with weights rather than a huge number of hyper-parameters. It's considered to be among the best designs for a vision model [13]. The libraries required for the VGG-16 model are imported, along with any additional dependencies and TensorFlow or Keras. To define the model, it loads pre-trained weights from the 'imagenet' dataset and imports the VGG-16 model from Keras applications [14].

Fig. 3 Class Distribution after the SMOTE

VGG-16 model are imported, along with any additional dependencies and TensorFlow or Keras [26]. To define the model, it loads pre-trained weights from the 'imagenet' dataset and imports the VGG-16 model from Keras applications. VGG-16 model's pre-trained 'fc2' layer's output. The term "fc2" designates the VGG-16 architecture's second fully connected layer. has a softmax activation technique together with an additional thick layer. The layer has the name Predictions. The input layer comprises the VGG-16 that displays an image of 224 by 224 pixels and three RGB color channels (None, 224, 224, 3) [15].

It consists of MaxPooling2D (max-pooling layers) and Conv2D (convolutional layers) [22]. Every block has a max-pooling layer (block1_pool) after two convolutional layers (blockX_conv1 and blockX_conv2). The input images can be used to observe the hierarchical characteristics of these layers, and max-pooling lowers spatial dimensions. The flatten layer transforms the three-dimensional spatial data into a one-dimensional vector. Here, the output of the last max-pooling layer is flattened into a vector of 25,088 elements. They all use Relu's activation function and have 4,096 neurons. The high-level features that the CNN layers acquired are included into these layers. The output layer is responsible for producing the final projections. The variety of classifications it has been trained to classify is reflected in the five neurons. There are several activation functions employed for different jobs; multi-class classification often uses SoftMax activation [16].

Total params: 134281029 (512.24 MB)

Trainable params: 134020869 (511.25 MB)

Non-trainable params: 260160 (1016.25 KB)

The weights and biases are represented by the total parameters. While non-trainable parameters are usually fixed, trainable parameters are those that learn during training. The depth and intricacy of the VGG-16 design are reflected in the significant number of parameters.

Hyper parameters are:

Batch size is 32, Initial learning rate is 0.01, Dropout is 0.5,

Minimum learning rate is 0.0001 and Epochs are 20.

2.4 Model testing and training

The predicted shape of the images being used is specified by the following shape (224,224,3), which should be included in an input layer. The VGG16 model that was pre-trained by Keras is imported, and its weights were trained on the ImageNet dataset. 20 epochs were used to train the model. In a neural network, an epoch is a complete pass over the entire training dataset. The model receives each sample from the data collection precisely once every epoch, which aids in updating the model's weights and improving performance. ADAM, the optimizer, was utilized. It modifies other neural network parameters such as weights and learning rate. It is stated that ADAM is highly effective and reduces the length of training. Trained with a Batch Size of 32, Learning Rate of 0.001, a relu and Softmax active layer, and a categorical cross-entropy loss function. After several tests, the balanced data model achieved results of 79.88% accuracy and 70.23% loss. Whereas the unbalanced data model achieved results of 71.65% accuracy and 79.5% loss.

III. RESULTS AND DISCUSSION

3.1 Dataset

This study used the DR 224×224 Gaussian Filtered dataset obtained from the APTOS 2019 Blindness Detection Competition on Kaggle [12]. It is essentially a set of processed retinal scans that are predominantly meant for diagnosing cases of DR. To ensure consistency with different pretrained deep learning models, all the images have been converted to 224x224 resolution [25]. Each of these five divisions is represented by a particular stage or severity category of DR. The train.csv file aids in segmentation and links images to the appropriate severity rankings. supporting the smooth integration of images into the deep learning pipelines that are currently in place and investigating various impairment levels. Uniformly applied image sizes are also organized in a structured manner, which can be mapped into the existing category of diagnosis for diabetic retinopathy [17].

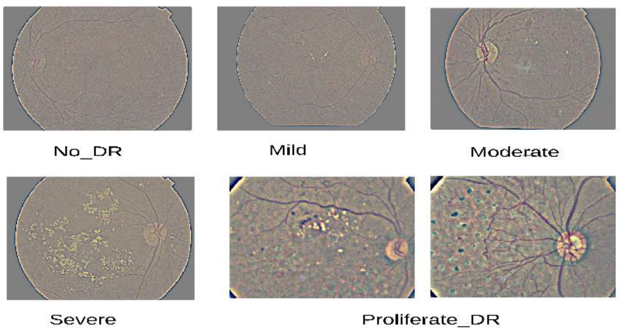


Fig. 4 Different levels of Diabetic Retinopathy

The approach was able to categorize the extent of DR in the provided pictures and categorize them on a scale from 0 to 4. After the trials were over, we obtained the experiment's data, which we utilized to show the precision of the project. For the balanced training dataset, we employed the VGG-16 architecture; the outcomes are displayed in Table-1. The balanced dataset sizes for training and validation are 3448 and 862. The Optimizer ADAM and the Categorical Cross Entropy loss function are utilized. To train and assess the model, the number of epochs and the learning rate parameter are modified. The model fared better with a learning rate of 0.0001, epochs 20 with an accuracy of 79.99%, according to the proposed balanced data. For unbalanced data model accuracy is 71.65%. From Table-2 the existing balanced data model accuracy is 71 to 73%. The Proposed model fared well in comparison to the existing model.

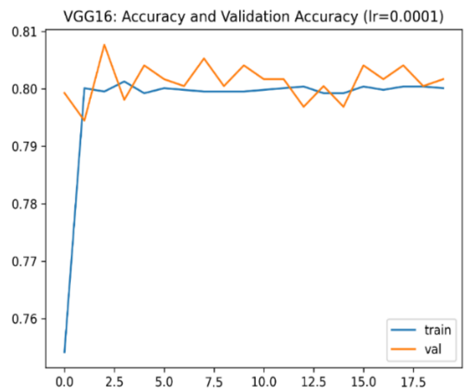
Table 1 proposed model parameters

Training balanced dataset size	3448
Validation balanced dataset size	862
Loss function	Categorical Cross Entropy
Optimizer	ADAM
Learning rate	0.0001
Epochs	20
Balanced data model accuracy	79.99%
Unbalanced data model accuracy	71.65%

Table 2 Existing model [2]

Balanced data model accuracy	71 to 73%

According to the results, employing this model may be a useful technique for early diagnosis of diabetic retinopathy. They also imply that other eye-related medical disorders may be detected using these kinds of models. As seen in the table above, VGG16 provides more accuracy than state-of-the-art approaches [2]. Now we'll look at the VGG16 Accuracy and Loss graph.



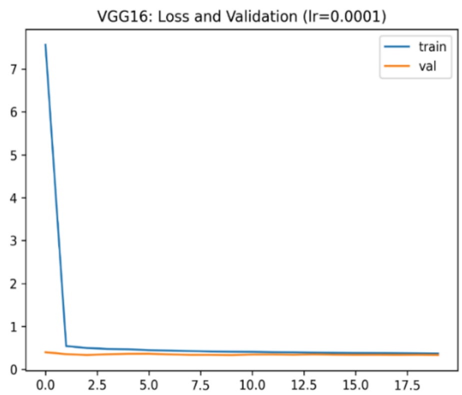
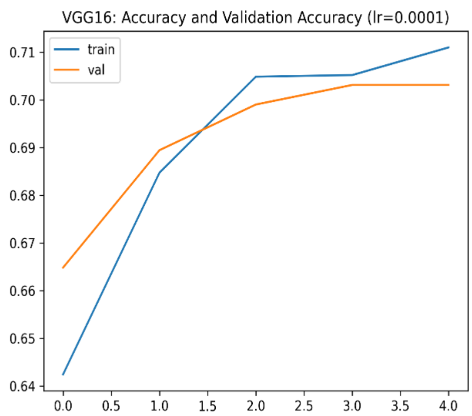


Figure-5(a) Accuracy and Validation Figure-5(b) Loss and validation

The accuracies and losses of balanced data VGG16 model are depicted in the figures fig.5(a)& fig.5(b).



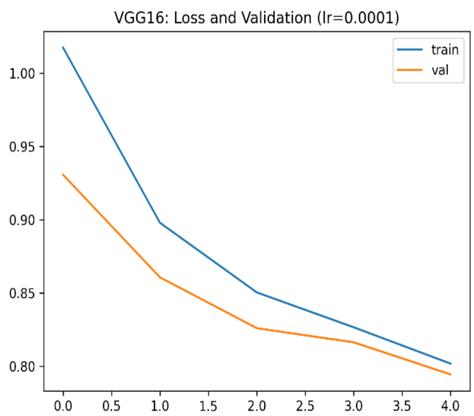


Figure-5(c) Accuracy and Validation Figure-5(d) Loss and Validation

The accuracies and losses of unbalanced data VGG16 model are depicted in the figures fig.5(c)& fig.5(d).

IV. CONCLUSION

We have demonstrated how fundus color pictures are used to develop the VGG-16 model for diabetic retinopathy. Our research demonstrates the practicality of using deep learning to solve this issue. The VGG-16 framework identifies diabetic retinopathy and provides information on the seriousness of the condition. The accuracy value obtained was 79.99% higher than the accuracy value of the unbalanced data VGG16 model, which is 71.65%, when comparing the VGG16 architectural model with the SMOTE technique on epoch 20. Professionals who are trying to identify this sickness early may find this model helpful. Comparable models for the diagnosis of many diseases, particularly those affecting the eyes, can be created. This could help prevent blindness that lasts a lifetime and help detect some illnesses early. In order to create a more precise DR detection system, the proposed work was broadened to include an investigation of DL models and their architectures. The future direction is to improve and reduce time constraints to enhance detection. Further exploration is necessary to further enhance our model.

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