International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

Artificial Intelligence and Deep Learning-Based System Design for Diabetic Retinopathy Classification

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Abstract— One of the biggest causes of avoidable blindness throughout the world is diabetic retinopathy (DR). There is a significant unmet need to test all diabetes patients for DR, and many instances of DR go undetected and untreated. In order to automate DR screening, this research aimed to create reliable diagnostic technologies. In order to reduce the pace of vision loss, it is important to refer eyes suspected of having DR to an ophthalmologist for further assessment and treatment. The primary goal of this research is to improve the classification accuracy for Diabetic Retinopathy (DR). In this script, we present a new neural network model for DR forecasting. The suggested model's accuracy in identifying DR phases was measured against that of regular and ensemble-based models. Various benchmark datasets, including MESSIDOR, IDRID, and APTOS, are used in the studies. The suggested DRPNN algorithm outperformed the competition in experiments assessed using industry-standard criteria.

Keywords- Diabetic retinopathy, Avoidable blindness, Diabetes patients, DR screening, diagnostic technologies, Vision loss, Ophthalmologist assessment, Classification accuracy, neural network model

I. INTRODUCTION

Artificial Intelligence is a branch of Computer Science that has gained boundless popularity in recent decades due to its inter-disciplinary, multi – disciplinary and Trans – disciplinary applications as well. AI applied to any domain is a field by itself. The power of AI has been harnessed for providing robust solutions to challenging problems in all domains including Medicine, Agriculture, Civil Engineering, Robotics, Information Security, Education and much more. The unlimited potential of artificial intelligence coupled with digital image processing techniques have revolutionized the health sector in providing personalized and timely health care to people of all ages. With the advent of powerful medical imaging equipment, there is a massive increase in the generation of medical images establishing a huge database for medical analysis and disease prediction. Artificial Intelligence holds out the promise of new breakthroughs in medical research. AI has made outstanding contributions in the field of healthcare. Prediction of 3D structure of proteins in drug discovery process, identification of unrevealed association between viruses and stem cell classification, prediction of chronic diseases are a few recent medical innovations. Machine Learning (ML) is the subfield of AI that is capable of building intelligent models from analyzing massive amount of data- through training and testing computational pipeline. It includes supervised, unsupervised, semi – supervised and reinforcement learning paradigms.

Medical Image Processing

Medical Imaging is the one of the conventional techniques, which helps to view the interior parts of the body for effective diagnosis. It is considered to be one of the major innovations of the healthcare systems and led to the interdisciplinary field of medical image processing. It includes end to end process right from data acquisition to clinical interventions and digital communication of medical images. Computer Aided Diagnosis (CAD) helps the specialists on their diagnosis procedure with greater accuracy and efficiency. It enhances the raw medical data with the implementation of problem specific approaches for further analysis.

Diabetic Retinopathy

Diabetic Retinopathy is one of the diseases that have created major impacts among diabetic patients. It is a common critical complication of diabetes mellitus which affects the human eye leading to blindness in severe stage. In industrialized countries like US, there are 29 million Americans, in the age group of 25–74 years living with diabetes mellitus (DM) and 33% of them are having the symptoms of diabetic retinopathy. Long Diabetes injures the retinal blood vessels and thereby impairs the visibility of a person, leading to diabetic retinopathy. Diabetic retinopathies move into two main pathological stages such as PDR (Proliferative Diabetic Retinopathy), NPDR (Non-Proliferative Diabetic Retinopathy) and four clinical stages. The early stages of DR, which are divided into mild, moderate and severe phases, are referred to NPDR. Micro aneurysm (MA), which denotes the emergence of a tiny red dot in a circular pattern at the end of the blood vessels, is the initial stage, and in the subsequent moderate stage, the micro aneurysms progress into deep layers and cause a haemorrhage in the retina that resembles a star.

Additionally, intra-retinal haemorrhages occur in the section of a particular vein with well known intra-retinal micro vascular anomalies during the severe stage. PDR is referred as the advanced stage of DR, with the occurrence of new blood vessels inside the retina in the form of functional micro vascular networks. The four stages of DR are visually represented in Figure 1.

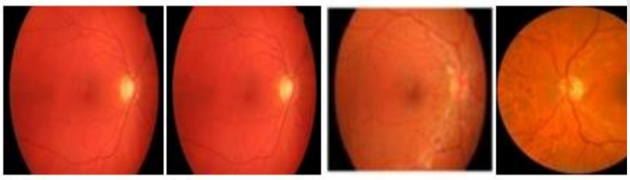

Figure 1: Classification of DR Severity Using Color images

Deep Learning Algorithms

Deep Learning is a branch of artificial intelligence (AI) that is modelled after the neuronbased neural networks seen in the human brain. It is more beneficial than machine learning (ML) methods since it requires less human intervention. Artificial Neural Networks (ANN) of robust solutions to image categorization issues, such as disease identification from biomedical images. Convolution Neural Networks (CNN), which are made up of neurons that self-optimize through learning, are among the most interactive ANN topologies. Every neuron will take in information and carry out an action that is largely utilized to address automatic recognition of various visual patterns. Convolutional layers, pooling layers, and fully-connected layers are the three types of layers that make up CNNs. Figure 2 depicts the fundamental structure of a CNN, and the layers are described in detail below.

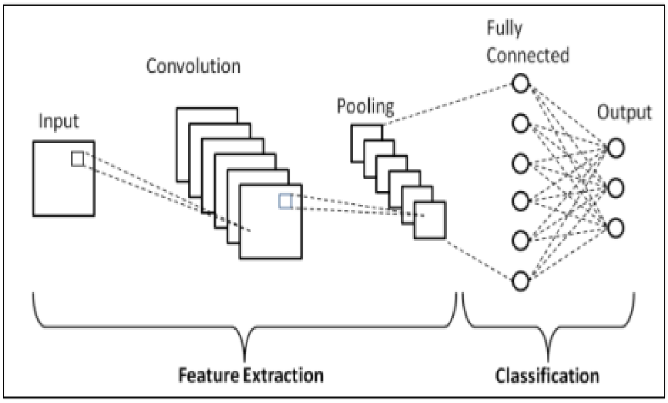

Figure 2: Basic CNN Architecture

Input layer: This layer stores the image's pixel values.
Convolutional layer: It calculates the scalar product of the input block and the filter of desirable size for feature extraction.
Pooling layer: The down sampling of the obtained output from the convolution layer is carried out by this middle layer between the convolution layers
Fully-connected layers: The network's top layer is a fully linked layer. Convolutional and down sampling approaches enable CNNs to alter the initial input layer by layer in order to provide class scores for classification and regression applications. A batch of weights from a pre-trained model is used to fine–tune a CNN. The effective methods for creating CNN models involve transfer learning and fine-tuning which allow a model that has been trained on a larger dataset to be utilized for a similar task that requires a smaller dataset.
Transfer learning allows for the transfer of pre-trained model features to new models without the need to learn new features. When fine-tuning is used in conjunction with transfer learning, transferred features are improved. There are Different types of pre-trained models namely Virtual Geometry Group (VGG16), VGG19, Alex Net, Mobile Net, Inception V3 and Dense Net -

121 and they are used for classifying different stages of DR classification using fundus image. This study aims to create more conceptual, automated ways for classifying DR in fundus pictures using machine learning and deep learning methodologies. Machine learning techniques are used to classify DR into its several phases, and its effectiveness is measured against industry standards.

Dataset Description

To experiment and evaluate the performance of our proposed methods, the researchers obtained the fundus images from the following benchmark datasets.

Comma Separated Values (CSV) File Datasets used for Machine Learning (i) MESSIDOR: This dataset collected from the UCI Machine Learning repository contains a total of 1151 instances, of which 540 records are represented as healthy and 611 records represent multi-stage cases (ii) Indian Diabetic Retinopathy Image Dataset (IDRID) The IDRID dataset offers ground facts about Diabetic Macular Edema (DME), Diabetic Retinopathy (DR), and healthy retinal architecture.

It includes the attribute data for pixel-level annotations of typical DR lesions and the optic disc, DME severity grading at the image level, and coordinates for the fovea and optic disc. Each CSV file has three columns that contain the image number, the X co-ordinate, and the Y coordinate. The X and Y co-ordinates correspond to the image's OD/center Fovea's pixels. (iii) Pacific Tele – Ophthalmology Society (APTOS) The normal retinal structures linked with all of the Diabetic Retinopathy (DR) symptoms are provided by the APTOS dataset. A doctor graded each image for the severity of diabetic retinopathy on a scale from 0 to 4, where the numbers signify the degree of the issue. It provides the attribute information for each image like No DR, Mild, Moderate and Severe. It contains training set images and test images in the separate CSV file with 13,000 images respectively.

Fundus Image Dataset for developing Deep Learning Models

E-Ophtha: This dataset contains 381 compressed images of which 148 have MAs and 233 images are normal healthy fundus images.

ROC (Retinopathy Online Challenge): This dataset contains 37 MA affected images and remaining 13 images are healthy.

DIARETDB1: This dataset contains 28 training and 61 test images in the form of uncompressed images acquired at 50◦ FOV.

IDRID: This dataset consists of total of 516 fundus images of dilated eyes collected at an ophthalmology clinic in Nanded, India, using a Kowa VX - 10α fundus camera.

APTOS: The Asia Pacific Tele-Ophthalmology Society (APTOS) consists of 3662 high resolution retinal scan images.

II. LITERATURE SURVEY

Diabetic Retinopathy is defined as micro vascular disease which creates the blockage in our retinal blood vessels when diabetic patients have high blood sugar value. It also blocks the main nutrition content from the retina tissues. Several automated techniques and models have been developed in recent decades to identify and grade different stages of DR from eye fundus images. This chapter summarizes the well – known research contributions on DR classification based on Machine Learning and Deep Learning.

DR classification with DR fundus images is becoming increasingly important in the medical field. Several works related to DR classification using machine learning are presented below.

Reddy et al. (2021) explored optimal algorithms for the prediction of diabetic retinopathy. They used Random forest, Decision tree, Adaptive boosting, Bagging and compared with proposed Support Vector Machine with Gaussian kernel. The results prove that this model achieves the best accuracy of 81.3 %.

Pelin et al. (2021) designed an application using six different decision tree-based (DTB) classifiers and different ensemble learning methods approaches namely Adaptive Boosting (AdaBoost) and bagging using Naive Bayes classifier. The experimental results achieve the higher accuracy score of 98.65 %.

Zun Shen et al. (2021) explored the methods for the prediction of DR by creating an impact on high-dimensional and small-sample-structured DR Dataset. The proposed SelStacking model was developed with XGB-Stacking model which is the combination of XGBoost and stacking. The proposed prediction model had outperformed existing methods with improved classification accuracy of 83.95 %.

Eswar et al. (2022) developed an optimal feature-based system for the prediction of retinal disease. The ensemble random forest was selected as an ultimate model to predict features-based diabetic retinal system based on its performance. It yields an accuracy of 0.975.

Ashwin et al. (2019) studied the identification and classification of diabetic retinopathy using Adaptive Boosting and Artificial Neural Network. For the purpose of DR detection and prevention, it compares traditional processes with machine learning techniques. Exudates are detected and classified by applying Adaptive Boosting (Ada Boost) classifier using selected features.

Prathyush gluria et al. (2022) offered a smart healthcare data-centric framework was constructed utilizing supervised machine learning techniques. The dataset containing 520 instances of diabetic patients and 17 characteristics is applied to an ensemble of several ML algorithms based on boosting and bagging. This ensemble model achieved better performance with F-Score values of 97.8% and 97.6 % respectively for boosted tree and bagged tree.

Jadhav et al. (2021) developed a rider optimization algorithm for feature selection-based diabetic retinopathy detection. Images are categorized using a Deep Belief Network (DBN)-based classification algorithm into four stages namely normal, mild, moderate, or severe. The Modified Gear and Steering-based Rider Optimization Method (MGS-ROA), an enhanced metaheuristic algorithm, selects the best features and adjusts the weight in the DBN. Additionally, performance comparison with current classifiers including NN, K-NN, SVM, DBN, and traditional classifiers is conducted. The accuracy of the proposed MGS-ROA-DBN is 30.1% faster than NN, 32.2% faster than KNN, and 17.1% faster than SVM and DBN.

Gadekallu et al. (2020) explained detection of DR using PCA –Firefly based deep learning model. To extract the key features PCA is utilized as a conventional scalar, and the firefly technique is employed to reduce the number of dimensions. The model shows good performance interms of Accuracy of 96 %.

Keerthiveena et al. (2019) examined the use of the Firefly algorithm to the detection of diabetic retinopathy. A screening method has been developed to differentiate between normal and abnormal fundus pictures. A fuzzy C-means clustering method and a match filter were used to segment the blood arteries. Different filter sizes were able to capture blood vessels of varying diameters thanks to their line-like directional features. The proposed algorithm has been compared against state-of-the-art methods for early detection of diabetic retinopathy in an effort to improve classification results while making use of the fewest features feasible.

III. MATERIALS AND METHODS

Dataset Description

This work used three DR datasets MESSIDOR, IDRID, and APTOS for experimenting the proposed classification pipeline.

Methodology of Diabetic Retinopathy Prediction

In this work, the following steps are used for classification, which are Pre-processing, Feature Extraction, and ML-based Classification. The proposed methodology of this phase is depicted in Figure 3.

(i) Pre-Processing Pre-processing is one of the important steps crucial for accurate classification. In the proposed model, data imputation is applied to replace the NaN values to retain most of the information of the MESSIDOR, IDRID, and APTOS datasets.

In this research, data reduction and one – hot encoding preprocessing techniques were used to find the missing values and reduce the size of the DR Datasets.

(ii) Feature Extraction: Blood vessel area, exudates area, MA area, contrast, homogeneity, correlation, and energy were all taken into account during feature extraction. The proposed Improved Lasso feature selection algorithm described in the previous chapter was used to select significant features from the DR Datasets. Regularization methods generally reduce the risk of over fitting by reducing the variance or estimate, and improve prediction. Based on this methodology, features accomplish variable selection and regularization simultaneously by improving the predictive capacity and understand ability of the regression model through sparsity.

Proposed Diabetic Retinopathy Prediction using Neural Network (DRPNN) One of the best computational intelligence methods used in pattern recognition, data mining, and machine learning is Artificial Neural Networks (ANN). It creates very effective networks that can surpass the majority of other algorithms. Three layers - the input layer, the hidden layer, and the output layer make up the basic structure of simple ANN also known as Multi-Layer Perceptron (MLP).

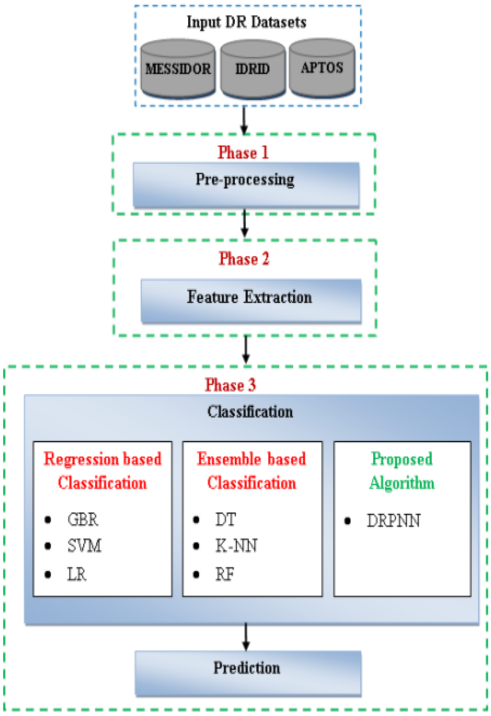

Figure 3: System Architecture – Classification

This research work proposed novel Diabetic Retinopathy Prediction model using Neural Network (DRPNN). It is constructed with an optimal number of neurons in every layer that are computed through weighted variables and input variables. The summarization of the weighted inputs is applied through the activation function. The DRPNN model has the sigmoid transfer function as its activation function. In the output layer, the Softmax transfer function is used to deal with DR that has more than one classification. It

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was possible to get the best level of accuracy by revealing many secret layers. Making the secret layers bigger helps make the ranking more accurate. Cross-entropy is used to judge how well a neural network model works for a cost function. Cross-entropy is used instead of squared-error cost functions because it is much more useful in real life. The DRPNN Cross-Entropy is shown in Figure 4.

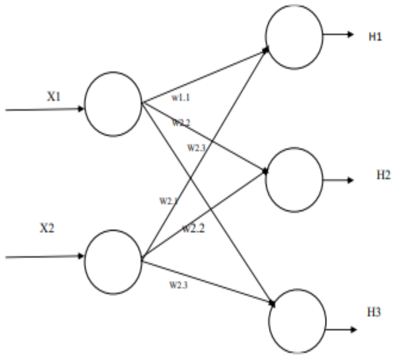

Figure 4: DRPNN Cross-Entropy Model

Hyper-parameters used in the DRPNN Model

The proposed DRPNN model uses the following hyper-parameters, which are fine-tuned as presented in the Table 1.

Table 1: hyper-parameters values

S. No	Hyper-Parameters	Value
1.	Batch Size	25
2.	Learning Rate	0.001
3.	Optimizer	Adam
4.	Activation function	Relu
5.	Loss function	binary-cross entropy
6.	Epochs	50- 200
7.	Accuracy	91-93 %

Algorithm 1 Proposed DRPNN

Input: DR Datasets (MESSIDOR, IDRID and APTOS)

Output: Classification of DR images

Begin

Step 1: Load the DR Dataset

Step 2: Split the Dataset into training and testing set Phase - I: Pre-Processing

Step 3: Pre-process the dataset using data reduction and one-hot encoding techniques Phase-II: Feature Selection

Step 4: Select the features from DR data set using Improved Lasso Phase - III: Classification using DRPNN

Step 5: Build the basic with three hidden layers

Step 6: Hypertune the parameters

Step 7: Train the model using the training dataset

Step 8: Validate the performance of ANN with test dataset

End

IV. RESULTS AND DISCUSSIONS

The experiments are run on Windows 8.1 using Python with the standard datasets. Table 2 represents the performance comparison of existing classification algorithms and the proposed DRPNN in terms metrics

Table 2: Performance Analysis and comparative analysis of Classification Algorithms

Dataset	Classifiers	Precision	Recall	F-Score
MESSIDOR	k-NN	84	79	81
	RF	87	81	83
	DRPNN	91	86	88
IDRID	k-NN	83	77	80
	RF	86	81	82
	DRPNN	90	85	87
APTOS	k-NN	86	79	82
	RF	89	83	80
	DRPNN	91	86	88

It is worth nothing that the proposed DRPNN classifier achieves the highest values for precision, recall, and F-Score than other ML-based classification algorithms with respect to MESSIDOR, IDRID, and APTOS datasets. Figure 5 show the graphical representation of the performance measures for MESSIDOR, IDRID, and APTOS datasets respectively.

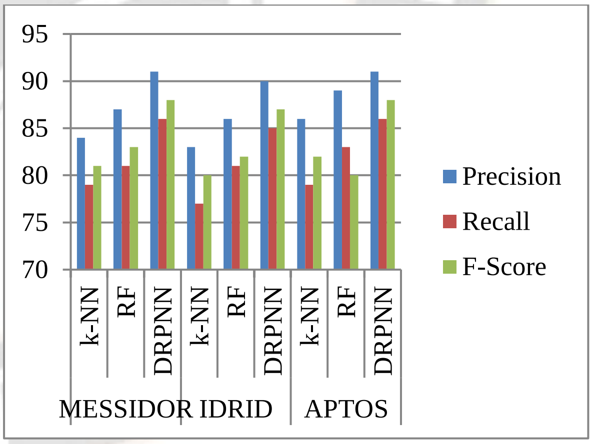

Figure 5: Comparative Analysis and Performance Analysis of Classifiers using IDRID Dataset

Table 3: Execution Time for Classifiers

Dataset	Classifiers	Execution time
MESSIDOR	k-NN	910
	RF	840
	DRPNN	760
IDRID	k-NN	919

	RF	830
	DRPNN	760
APTOS	k-NN	860
	RF	810
	DRPNN	740

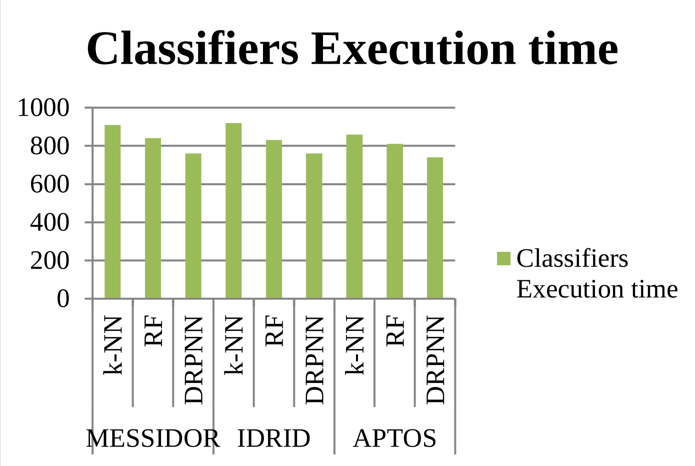

Figure 6: Execution Time for Classification Algorithms

V. CONCLUSION

In this paper, Diabetic Retinopathy Prediction using Neural Network (DRPNN) algorithm was proposed for DR classification. The proposed algorithm was compared with widely used existing machine learning models, which are regression-based classification and ensemble-based classification using different benchmark datasets such as MESSIDOR, IDRID, and APTOS. The experimental results showed that the proposed DRPNN algorithm performs in an efficient manner than other techniques.

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