European Journal of Molecular & Clinical Medicine

ISSN 2515-8260 Volume 10, Issue 1, Winter 2023

RULE MINING BASED CLINICAL TRIAL USING TRANSFER LEARNING APPROACH WITH THE GRADING OF DIABETIC RETINOPATHY IN HOME-CENTRIC ENVIRONMENT

Dr.C.Saravanabhavan[1,*]
Professor and Head, Department of CSE, Kongunadu College of Engineering and Technology, Trichy,Tamil Nadu 621215, India
hodcse@kongunadu.ac.in

MA.Swedhaa[2] ,
(PG Student)
Department of Computer Science and Engineering
Kongunadu College of Engineering and Technology
Tricy,India
swedhaamathivanan@gmail.com

Dr.P.Preethi
Assistant Professor, Department of CSE, Kongunadu College of Engineering and Technology, Trichy,Tamil Nadu 621215, India
preethi1.infotech@gmail.com

Mrs.K.M.Swarna Devi[4]
Assistant Professor,
Department of CSE, Kongunadu College of Engineering and Technology, Trichy, Tamil Nadu 621215, India

Abstract

The features from the fundus pictures' optic disc must be precisely located before landmark features included in the fundus images can be identified. According to the severity of the DR, existing research employed a variety of Artificial Intelligence (AI) strategies for screening and diagnosing DR sooner to protect diabetic patients from going blind. In contrast to the real-world optimization strategy, the current models, while effective, had limitations related to time consumption and premature convergence. As a result, the Multi-class Transfer Learning that has been proposed is updated to improve performance based on its fundamental design. The model was trained to find solutions more effectively thanks to the higher convergence. The suggested approach gets around constraint problems and improves accuracy with better feature selection. In comparison to the current transfer model, which achieved 98.94% accuracy for DIARETDB1, the suggested method achieved an accuracy of 97.46%. The e-ophtha dataset, however, achieved accuracy of 98.91%. The predicted algorithm can be integrated with any device at home-centric environment.

Keywords: Retino, e-ophtha, transfer learning, ResNet, Diabetic Retinopathy and ImageNet.

Introduction

Diabetic patients are predicted to reach 415 million worldwide, with one in every ten individuals suffering from the disease, according to [1]. Numerous individuals have received a diabetes diagnosis in the last ten years. Several eye problems may develop as a result of diabetes, including diabetic retinopathy (DR). Blood vessels in the eyes were destroyed by Dr, causing progressive and sometimes irreparable blindness in individuals. About 45% of diabetes patients get eye diseases, which affect one eye vessel. Microaneurysms, secretions (hard and soft), hemorrhagic, and cotton ball patches in are common in DR [2]. As a chronic illness with several phases, DR results in blindness for its victims. This study focuses on applying transfer learning techniques to identify diabetic retinopathy. It also uses a variety of indicators to evaluate multiple transfer learning methods.

Related Work

Deep learning has also been employed. [3] say they've employed machine learning to identify DR before, but the results were mediocre. The authors of the new research employed CNNs and an ML technique to develop a strategy that offers the best results. The new correlations between the pictures that are provided to the algorithm were discovered using CNNs. The illness database made available to the system for this investigation is separated into three categories macular edema, eyesight DR, & possessing no DR. There is a scale that ranks the severity of symptoms from 0 (lowest) to 5 (highest). In the end, the suggested technique divides the pictures into three categories: negative DR, harmful and extremely frightening DR, and making mistakes in pictures of poor quality.[4] used DL with 8 CNNs to identify early diabetes mellitus.

[5] detected DR using DL and CNNs. The author selected two data sets and used vision-based methods for classification, separation, and identification, which is the most difficult task since minute DR-related features must be recognized. CNN's are used to train the classifier model, which is then integrated with a deep layered. The network creates a binary classification, and the extraction of features is the basis for its training. The quality evaluation module, which measures the sensitivity, is shown in retinal pictures after they have been rendered it. Augmented pictures are supplied into the DRs model, and 2 different pictures are integrated for accuracy. The performance of the authors' suggested technique is superior on a bigger database.

A unique DL strategy known as the deep network patch-based technique has been put out by [6]. Deep CNNs patches are used to classify images as having or not having lesions. With this method, a probability of a lesion's existence is generated. DR patients often have microaneurysms and hemorrhages in the first stage, and the technique prefers to pinpoint these first. They are known as red lesions in writing. It is difficult to choose another input sample, thus by creating a two-stage method, the accuracy of classification is improved. When data collection grows, writers suggest that were moderate it. The general strategy used by the study's authors is to first do picture preprocessing and then, use adaptive threshold algorithms to pick the lesions. Then characteristics are extracted from the photos, and they are identified as having diseases or not having diseases. The proposed model improves in aspects of Sensitivity range, as per the results were using the technique to multiple datasets.

Proposed Methodology

This work builds, executes, evaluates, and chooses the best framework for grading DR. The database is trained using the VGG16 design, ResNet50 V2 design, and EfficientNet B0 design of the CNN to do this work.

In addition to analyzing the efficiency of various ConvNets on the particular dataset, the offered study also suggests the ideal pre-trained networks for the categorization of DR. CNNs models are trained on the DRs Pictures database using a learning algorithm, which involves transferring data learned from one task to a semantic similarity one.

Database explanation

In the dataset [7] we're utilizing an open-source DR recognition database with 1000 photos divided 80:20, or 800 for training and 200 for validating. mild DR, Moderate DRs, No DRs, Proliferate DRs, and Severe DRs are the five categories into which the categorization is accomplished. Fig. 1 shows class pictures.

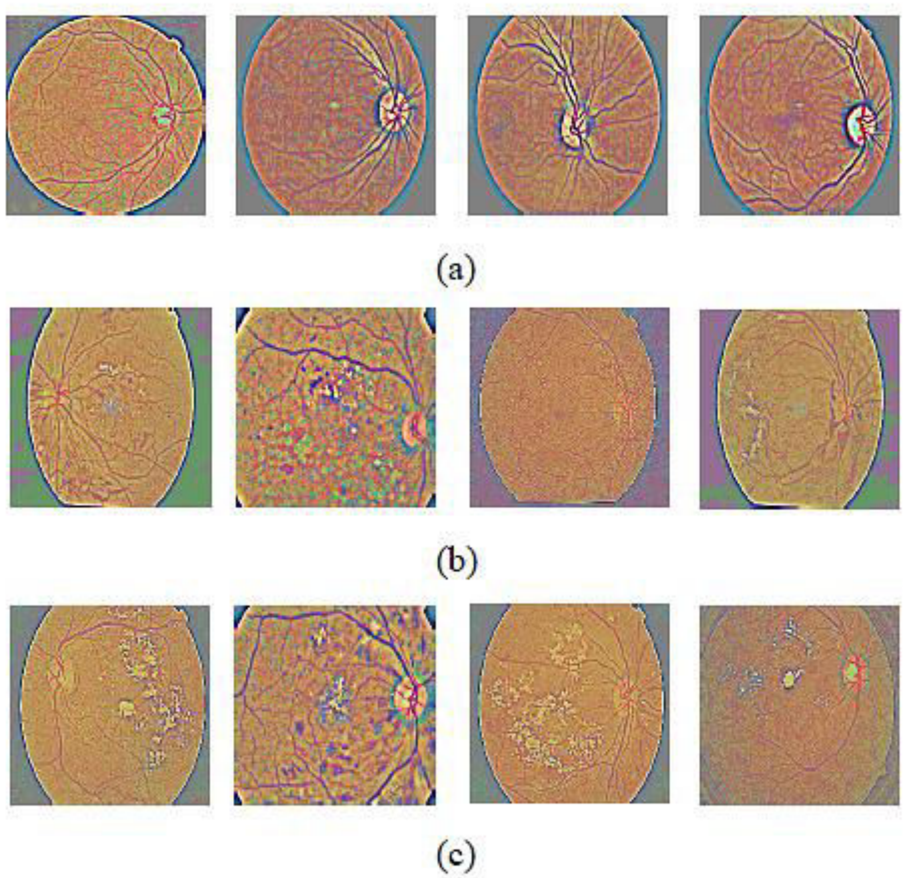

Figure 1: (a) No DRs, (b) Proliferate DRs, (c) Severe DRs Pictures.

Statistics Preprocessor

Since DLs need numerous annotated pictures for classification tasks, the information won't be adequate for state-of-the-art CNNs structures. Numerous data enhancement techniques are therefore used, including cropped, shear, rotating, and flipping [8]. After completing this process, the results are analyzed because a regular database ensures quicker learning resolution. The training workshop is carried out using the information from a single session since the database is tiny.

Framework of Networking

[9] We use CNNs with deep learning for picture categorization. There are different sorts of layers in their layered structures.

- Convolution as first level
- Sub-sampling as second level

- Fully Connected as third level

The study comprises training the database using VGG16, EfficientNet B0 & ResNet50 V2,. This models were created to be trained on most popular & substantial databases, such as ImageNet, Cifar-10, etc. We employ the abovementioned algorithms with pre-trained features for ImageNet.[10] to create a similar baseline for evaluation.

Structure of VGG16

The visual Geometry Phase is also known as VGG16. It was created using a CNNs framework by 11].

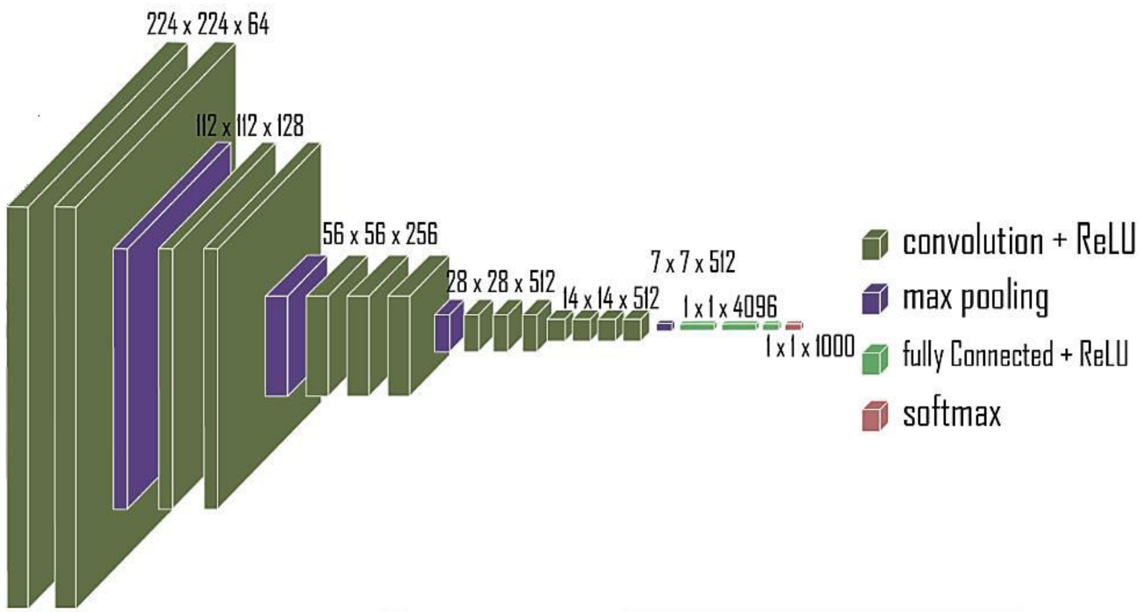

Figure 2: Structure of VGG16

In all, there are 12 levels in the structure of the VGG1structure in Fig. 2. The first Convolution layer has a depth of (224 *224 * 3). This picture is sent across several CNNs. The pre-trained value of a VGG16 architecture are around 500 MB in size because of its greater breadth and depth.

Structure of ResNet50 V2

ResNet, an abbreviation for Residual Networks, is a traditional NN that is used in a variety of picture recognition and vision-based applications. Resnets have 152 levels of intensity, as seen in

Fig. 3. We're using a 50-layer ResNet50 architecture with a connection attribute to avoid disappearing slopes [12].

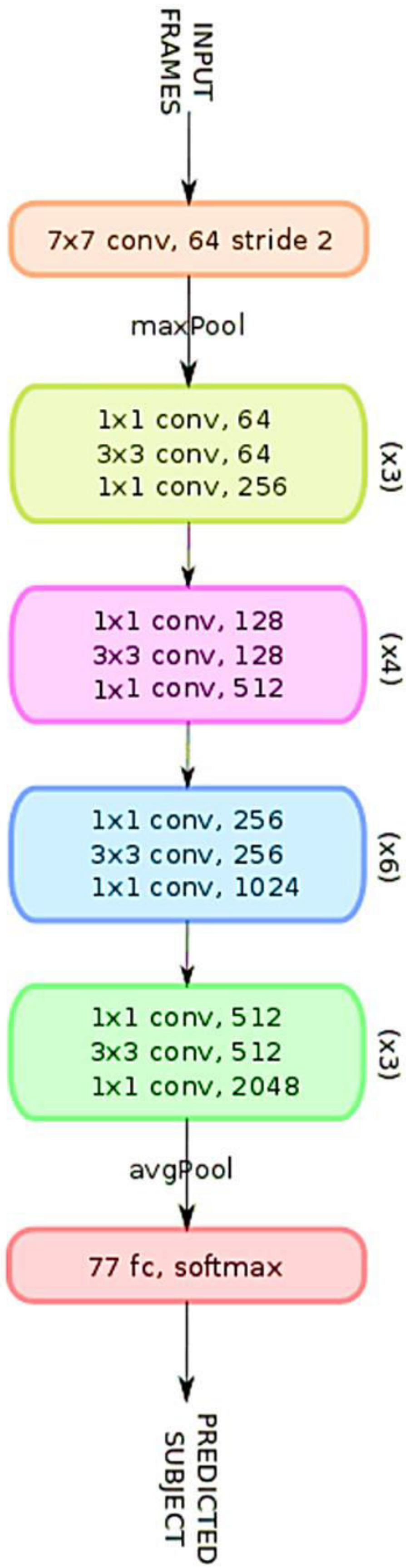

Figure 3: Structure of ResNet50 V2

Structure of EfficientNet

It is the most effective CNNs models, requiring the fewest FLOPS for interpretation. It performs well on ImageNet and normal picture analysis withTL. This study uses the baseline EfficientNet B0 architecture with inputs picture dimensions of (224 * 224 * 3) [13].

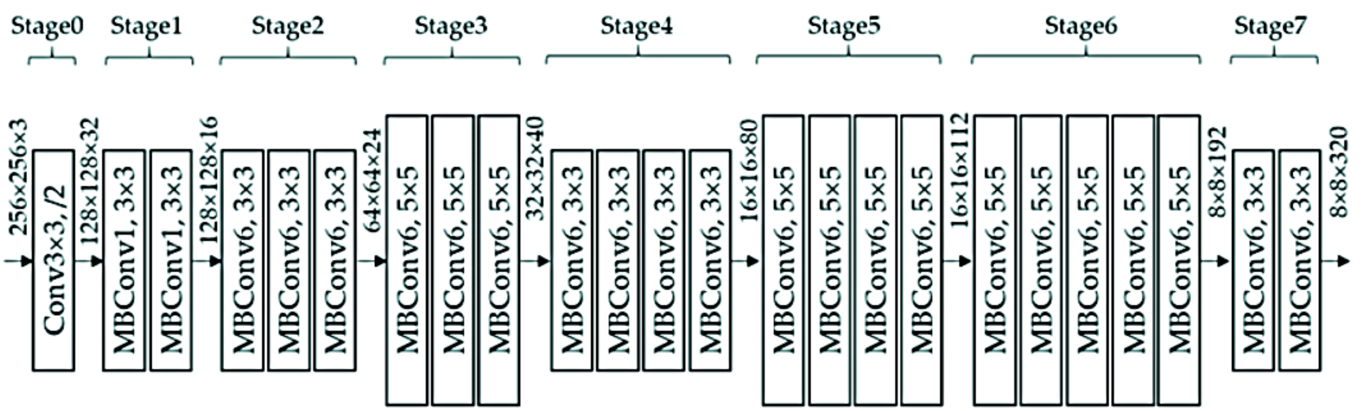

Figure 4: Structure of EfficientNets

Learning of Transfer algorithm

The learning of Transfer algorithm is use an ML approach that uses a framework developed for one task as the foundation for a model of subsequent, unrelated activity [14]. In deep learning tasks, utilizing existing DL approach as the foundation for CVs & NLPs activities is favored to reduce the higher computing and time resources required to develop NN techniques for these issues.

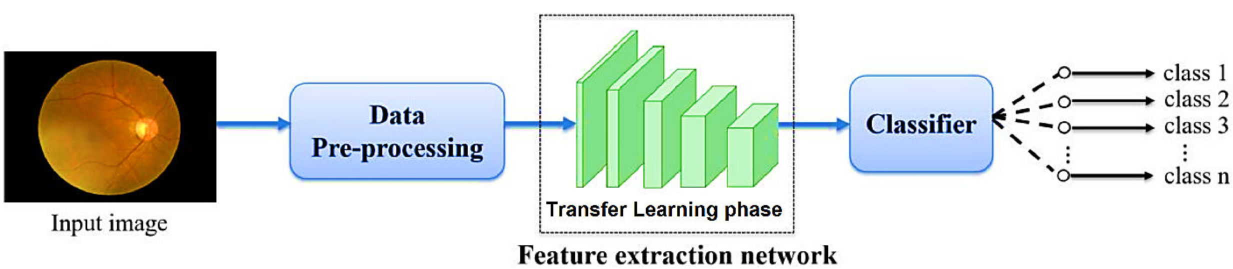

Figure 5: Transfer Learning data flow

This study employs designs that may be downloaded using TensorFlow's Keras. application module. Since we utilize the ImageNet-trained models' weights to retain learning information, we don't have to train the different levels, conserving time and energy. In order to do this, TensorFlow turns on the top layer, which corresponds to the classification surface in each network, and fixes the results of the bottom layer, preventing retraining. We then build a stack of four thick layers, each having a 256 depth, 128depth, and 128 depth and five vertex, the categorization level becoming the topmost part [15].

Process of Training

All CNN levels are converted to a sequence linear stack uses Keras' sequential approach API. An individual neural network is learned for 15 periods with such a call-back setup to assess the accurate rate, modifying the learning progress by 0.5 units every time it stagnates [16].

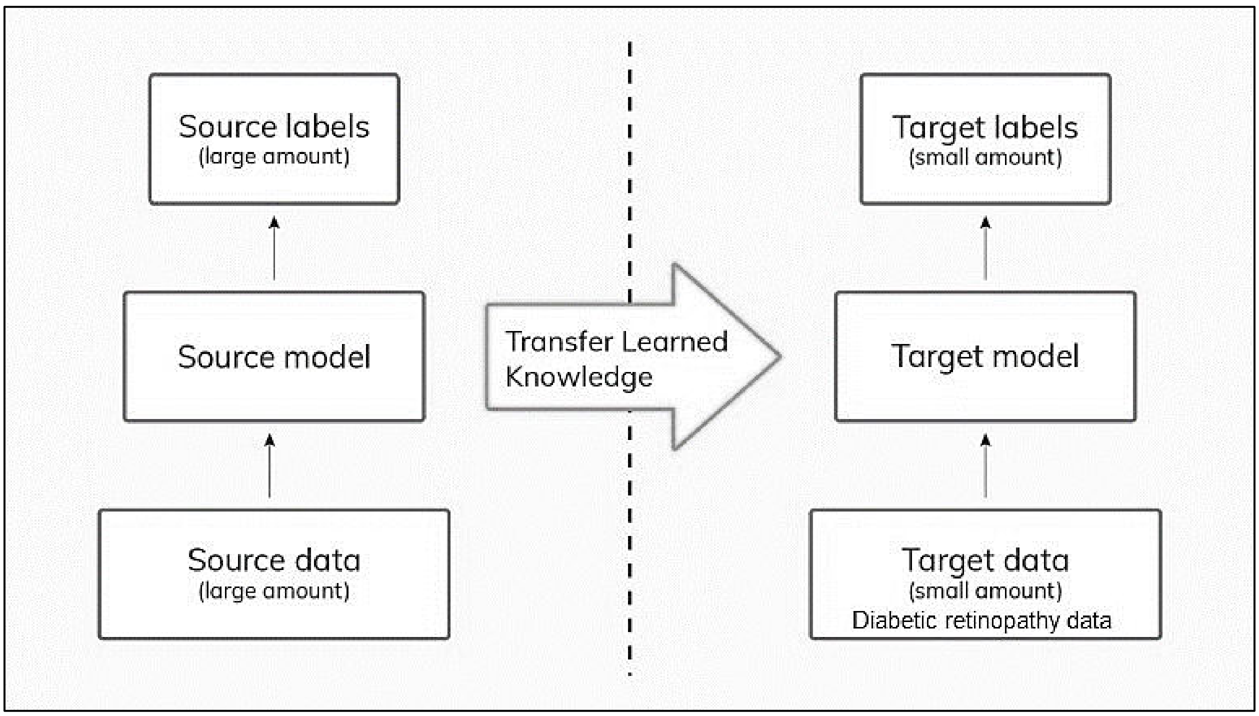

Figure 6: Process of Training

Optimization of Adam

Optimization techniques are methods that estimate the mistakes in forward propagation and assist in modifying a neural network's values and learning rates to reduce the loss. For the nodes to share a foundation for training, this study uses the Adam optimization. [17] The propulsion attribute of the RMSprop Optimization is introduced by Adam Optimization.[18] It manages the gradient component by splitting the information gain by the exponentially weighted moving mean of the squares gradients (ג).

Loss Function

A neural network uses a loss function to analyze prediction error. Simply put, a loss function is an intention function whose minimum must be found. Based on the learning target, Loss functions are divided into Classification and Prediction [19,20]. Because DR identification is based on multiclass, this study uses categories of cross-entropy losses.

Association Rule Mining phase

The major problem from the the literature is to the task of extracting frequent patterns from the dataset [21]. In order to solve the market basket problem, one must identify the relationships among a set of commodities in several baskets. One of the most popular association rule algorithms is the a priori algorithm [21]. The approach uses a level-based search to identify n + 1 item-sets from n item-sets [47]. In the candidate generation process, recurrent item-sets are extended. Candidates are then evaluated against the acquired dataset, and association rules are inferred as a result. The key tools used in the apriori approach are the breadth-first approach and hash tree structure. Classes value for diabetes in its early stages can be predicted quite effectively using extracted association rules. The strength of the extracted rule may be measured using several measures. They are,

- Support
- Confident
- Conviction
- Lift.

Our model's outputs were evaluated with the test set after being subjected to various classification methods to confirm model accuracy. To evaluate the prediction model's performance, we used performance measures.

Results and Discussions

Simulations of the recommended ensemble model's efficiency in DR recognition are run on a computer with 8 gigabytes of RAM, an Intel Core i5 CPU, and the Windows 10 (64-bit) operating system. The ratio of successful outcome expectations to all observed measures the accuracy of classification. Moreover, sensitivity estimates the number of genuine affirmations & specialization the number of actual negatives. The term "Eq." refers to a mathematical equation for F-score, specificity, & accuracy (1-4).

$$Accuracy = \frac{TP + TN}{TN + TP + FN + FP} * 100 \tag{1}$$

$$Specificity = \frac{TN}{TN + FP} * 100 \quad (2)$$

$$Sensitivity = \frac{TN}{TP + FN} * 100 \quad (3)$$

$$F - Score = \frac{2TP}{2TP + FN + FP} * 100 \quad (4)$$

Evaluation of various metrics

The outcomes of the suggested strategy without the use of feature selection algorithms are shown in table 1. The suggested method's effectiveness was assessed for some classifiers, including SVMs, K-NNs, RFs, DTs, NNs, and Ensemble classifiers. Without applying the suggested dynamic weighted CSA, accuracy was 97.73%, sensitivity was 97.33%, specificity was 95.47%, F-score was 96.94%, and precision was 96.55%. The current study employs SVM for identification, which isn't appropriate for huge datasets. The SVM failed due to overlapping class labels.

The outcomes of the suggested strategy using the algorithm for choosing features are in table 2. The SVMs achieved 94.80% accuracy, followed by KNN at 94.77%, RF at 96.37%, DT at 95.04%, and ANN at 98.17%. Similarly to this, 99.35% accuracy was measured using the ensemble technique. When data points had too many attributes, learning data samples underperformed. Due to its enormous dimensionality and difficulty in computing distance, the KNNs classifier struggled to perform as planned.

Table 1: Outcomes of the suggested technique produced without the use of feature selection techniques

Methods	Accuracy(%)	Specificity (%)	Precision (%)	Sensitivity (%)	F1- score(%)
Support vector machine	46.46	46.08	47.10	43.64	46.06
K-Nearest neighbor	93.19	93.49	92.46	92.64	92.55
Random forest	94.37	93.39	94.06	95.16	94.60

ISSN 2515-8260 Volume 10, Issue 1, Winter 2023

Decision Tree	93.43	93.49	94.50	92.39	93.23
Neural Network	96.92	94.88	94.08	95.79	94.93
Ensemble	97.74	95.47	98.55	97.33	96.94

Table 2: Outcome of the suggested technique using the feature extraction method

Methods	**Accuracy (%)**	**Specificity (%)**	**Precision (%)**	**Sensitivity (%)**	**F1- score(%)**
Support vector machine	94.80	94.95	97.32	93.25	95.24
K-Nearest neighbor	94.78	94.85	95.31	96.74	96.02
Random forest	96.37	96.42	93.12	94.19	93.66
Decision Tree	95.04	95.10	94.16	95.71	94.93
Neural Network	98.17	97.36	95.99	96.66	96.32
Ensemble	99.36	98.02	98.55	98.99	98.73

Table 3: Outcomes of different optimization techniques

Various Algorithm	**Accuracy (%)**	**Specificity (%)**	**Precision (%)**	**Sensitivity (%)**	**F1- score (%)**
PSO	90.03	89.91	97.71	89.07	90.37
ACO	91.26	91.58	95.50	92.61	90.41
FOA	93.79	94.17	93.95	92.37	93.53
SSA	96.62	94.32	95.59	95.91	95.27
PROPOSED	99.36	98.02	98.73	98.90	98.55

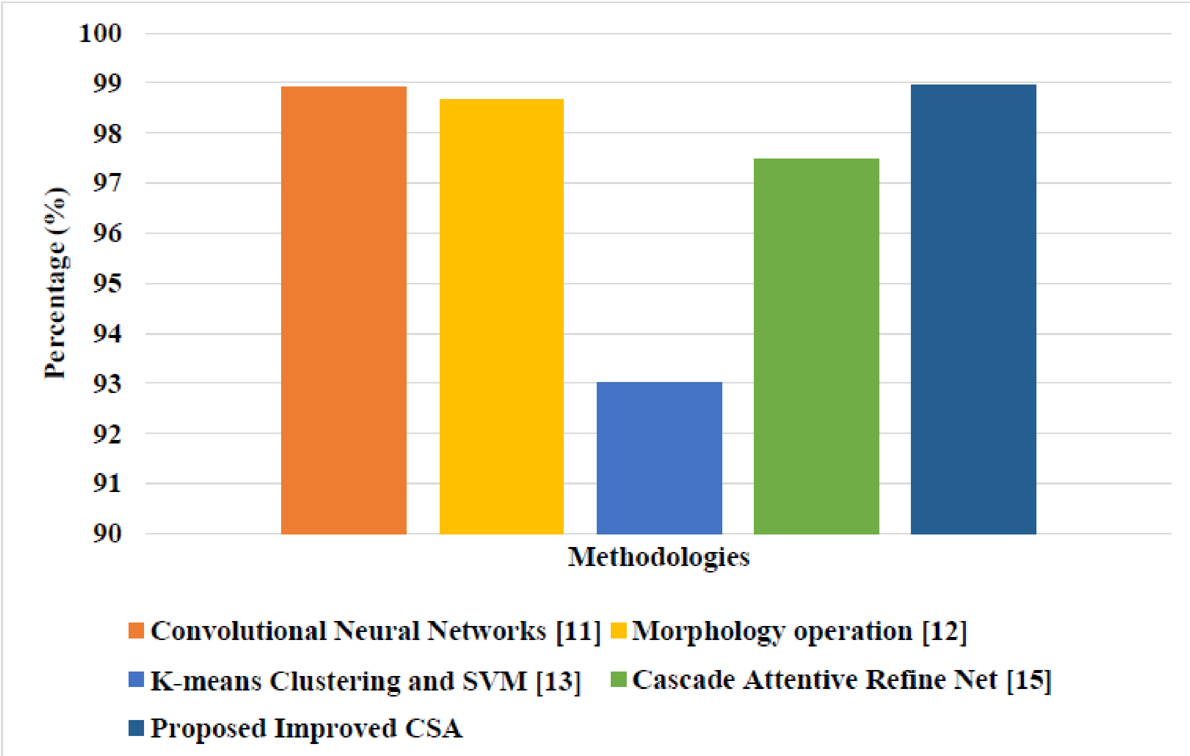

Figure 7: Performance of classifiers

Comparative analysis

Table 4 compares the proposed and current models based on their evaluations of their exactitude, precision, F-score, sensitivity, and specificity. Previous CNN's model lost characteristics due to the long path from input to output layers. Since the features were removed, the accuracy was 98.92%. The overlapping lesions on the original retinal picture, however, demonstrated an accuracy of 98.69%. The existing model, which employed SVM and wasn't designed for huge datasets, had a 93% overall accuracy. The difficult issues with an accuracy of 95.90 were not addressed by RF. In practice, ophthalmologists have trouble diagnosing such tiny, inconspicuous lesions, according to the created model, which had a 96.37 % accuracy for the e-ophtha database. DL The limited amounts of information may cause over-fitting in MA tracking systems based on DL

Table 4: Summary of Comparative Analysis

Database	Techniques	Accuracy in %	Precision in %	Sensitivity in %	Specificity in %	F1- score in %
DIARETDB1	CNN	98.52	96	-	-	96
	Operation in Morphology	98.49	-	-	-	-
	K-NNs and SVMs	94	-	90	81	-

	RF	-	95.91	73.94	-	-
E-ophtha	Cascade attentive Refine Net	97.47	-	96.53	98.46	-
	Multi-feature Combination	-	-	73	-	54.8
DIARETDB1 & E-ophtha	Proposed CSA	98.95	98.55	98.90	98.02	98.73

Conclusion

For early-stage diabetes prediction, we created a prediction system. Along with an a priori approach that identified correlations between different factors, trained classification methods were also used. A prediction model based on actual data was created by integrating frequent patterns and classification algorithms. Performance results demonstrated that, when compared to other models and earlier study findings, the integrative technique greatly improved model accuracy, leading to a predictive performance of 99.36% accuracy. This innovative method using the apriori strategy produced good outcomes. The datasets were trained, and the ophthalmologists validated the outcomes. When we take the extracted input in this case and contrast it with the conventional extraction method and the support method, we can see that the quality of the fundus images that were gathered has improved. The methodology is the most effective way of creating medications that are appropriate for the seriousness of the DR grade. Thereby, pharmaceutical companies will benefit from the proposed research as a consequence.

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