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DETECTION OF DIABETIC RETINOPATHY FROM RETINAL FUNDUS IMAGES USING IMAGE SEGMENTAION AND AUTOMATIC DEEP LEARNING MODEL

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Abstract: Early diagnosis and treatment of diabetic retinopathy (DR) are critical to minimize or avoid vision loss. Furthermore, automatically locating the areas of the retinal image that may have lesions can help experts in the detection process. This paper proposes a deep learning technique with an adequate image segmentation mechanism for recognizing DR from retinal fundus data. Initially, the fundus data is collected from the openly available dataset. Then, the Fast K-Nearest Neighbour Image Segmentation Module (FKISM) is developed to segment the retinal lesions from the collected fundus data. Then, Auto Feature Selection Convolution Neural Network (AFSCNN) is applied to perform automated feature, earning and classification of DR. Simulations are done to analyze the proposed system's effectiveness with the existing methodologies regarding classification metrics, and our proposed method illustrates superior performance by attaining higher outcomes in both training and testing contrasted to the traditional methods.

***Key words**: Diabetic Retinopathy, Retinal Fundus Images, Convolution Neural network, K-Nearest Neighbour, Deep Learning.*

1. INTRODUCTION

The major reason of vision loss in people with diabetes is DR; other conditions that can cause damage include neuropathy in the vascular and cataract vision, glaucoma, and age-related macular degeneration in the non-retinal and retinal visions [1]. Approximately 450 million people worldwide have diabetes mellitus (DM) today. In the past 20 years, the prevalence of this disease has almost doubled. The international diabetes federation estimates that by 2030, the prevalence of DM could increase by roughly 8%. It is approximate that by 2040, there will be about 600 million cases of diabetes worldwide, of which 200 million will be associated with DR, a chronic eye disease that causes blindness [2]. Prompt detection and management of DR are essential measures for overall health that can significantly reduce the risk of visual impairment. Instructions for effectively screening and analyzing the retinal fundus photographs to promptly identify retinopathy are essential [3].

To identify DR in colour fundus photographs of the retina, trained clinicians must examine the images. Identifying lesions exhibiting vascular abnormalities is a necessary step in diagnosing DR. This method of detection works well. However, it takes much time to manually analyze the images so that you will need the help of experienced clinicians [4]. In order to prevent further retinal damage, automation techniques that aid in the rapid detection

of DR can be used to determine the appropriate course of treatment [5]. The use of artificial intelligence in healthcare systems has grown in importance. Deep learning (DL) techniques have proven successful, particularly in medical image processing and analysis. Convolutional neural networks (CNNs) are one type of DL model that has shown potential in solving DR classification problems and expediting the process while yielding accurate predictions [6]. Using an efficient image segmentation model and an awareness of its strengths, CNN is used in this work to accurately diagnose DR from retinal fundus images and categorize cases according to severity.

The rest of the manuscript is listed as follows: The survey of DR detection techniques is presented in section 2. A detailed overview of the proposed systems is provided in Section 3. Section 4 provides a performance evaluation of the suggested and current systems, and Section 5 provides the conclusion.

2. LITERATURE REVIEW

Ramzi Adriman *et a*l. [7] presented the recognition and classification of DR by employing DL and texture features (DLTF). Initially, the system extracted the texture features from the fundus data using local binary patterns. Then, it used state-of-the-art DL techniques such as DenseNet, ResNet, and DetNet for detection and classification tasks. Simulations on the benchmark dataset showed that the considered DenseNet, ResNet, and DetNet attained an accuracy of 84.05%, 96.35%, and 93.99% respectively. **Akanksha Soni and Avinash Rai** [8] categorized the DR levels from fundus images using a machine learning system (DRML). The ocular image was pre-processed using a histogram equalization procedure, and the k-mean clustering technique was used to segment the improved image. This was followed by classifying normal and anomalous regions of the ocular image using SVM and the random forest algorithm. Compared to the SVM, the random forest classifier's 96.62% recognition rate indicates an excellent and reliable result. **Anas Bilal *et al.*** [9] suggested a two-stage approach called U-net and DL (UDL) for automated DR classification. The system initially enhances the quality and quantity of the image using pre-processing and data augmentation. Then, optic disk and blood vessel segmentation was carried out using two independent U-Net models. Then, the feature extraction and classification of segmented fundus data was done using the symmetric hybrid CNN-SVD. The system was tested on Messidor-2, EyePACS-1, and DIARETDB0 datasets and attained 94.59%, 97.92%, and 93.52% of accuracies for recognizing DR.

Ashish Bora *et al.* [10] presented a DR system using two versions of a DL (DRDL). Either a set of color fundus photographs with three fields or one field served as the input for both versions. Every patient underwent validation on one randomly chosen eye from each of the two datasets: 3678 eyes with known outcomes of internal validation set from EyePACS and 2345 known outcomes of external validation set from Thailand. The three-field DL system's area under the receiver operating characteristic curve in the internal validation set was 0•79 (95% CI 0•77–0•81). **Nagaraja Gundluru *et al.*** [11] presented a Harris hawk's optimization with DL (HHOD) for DR recognition. The system initially reduced the dimensionality of the dataset using principal component analysis, and the HHOD was used to perform feature selection and classification. The results attained by HHOD were far better than the existing techniques regarding classification metrics.

3. PROPOSED METHODOLOGY

This paper proposes a DL model with an efficient segmentation mechanism for DR detection from retinal fundus photographs. The modules developed for the segmentation and classification of DR are FKISM and AFSCNN. Initially, the FKISM module is used to distinguish and locate different retina image segments from the fundus images obtained from the dataset, reducing the computational complexity by mitigating the area of interest. After segmentation, the AFSCNN module was used, a kind of auto feature selection predicated CNN

that classifies the segmented regions into several DR levels. The proposed system's workflow is given in Figure 1.

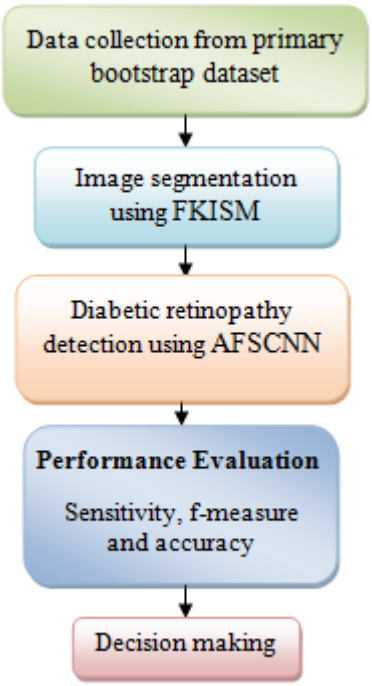


Figure 1: Workflow of the proposed system

3.1 Data Collection

The system initially prepares a dedicated primary bootstrap dataset (PBD) based on the experts' impressions of the complete dataset. The samples for the PBD dataset are selected randomly without any count constraints to evade the number of data collected.

3.2 Image Segmentation

The system segments retinal lesions from the collected fundus images using FKISM. Medical image segmentation offers several advantages; one is its ability to isolate only the areas required for a more accurate analysis of anatomical data. The K-nearest neighbours (KNN) algorithm is a potent and approachable machine-learning method for handling problems with regression and classification. KNN uses similarity design to predict a new data point's label or value by considering its k-closest neighbours in the training dataset. Based on instance-based learning, it functions. Due to the training set's prolonged usage and lack of use in model construction, this method is known as the "lazy learner". A class label with the most comparable attributes is given to each pixel. One or more class labels are assigned to each pixel, thus the term "soft approach". Selecting an optimal k-value in KNN to achieve the maximum accuracy in image segmentation is always challenging; since the PBD is precisely labelled, the initiation process commences with higher accuracy and precision. So, the proposed system uses the algorithm below to select optimal k-values in KNN, enhancing the system's accuracy in DR detection and classification.

Algorithm 1: Optimal K-Value Determination

Input: PBD

Output: Optimal K-Value

Step 1: Let η_{PBD} be the number of records in the PBD

Step 2: Calculate initial value of $k = {}^{1}/_{4} \times \eta_{PBD}$

Step 3: Increment the Value of k by 1 if it is Even

Step 4: Let tp, tn, fp, fn are the true positive, true negative, false positive and false negative values

Step 5: Repeat

Step 6: Compute $Precision = \frac{tp}{tp+fp}$

Step 7: Compute $Recall = \frac{tp}{tp+fn}$

Step 8: Compute $FScore$ as $\frac{2}{\frac{1}{Precision}+\frac{1}{Recall}}$

Step 9: Determine the Value of k by equation 1

Step 10: Repeat to Step 5 until$k < 7$ and $\frac{tp+tn}{tp+tn+fp+fn} > 0.9$

Step 11: Return k (optimized)

The K-determination equation is as follows

$$k = \begin{cases} (2 \times k) + 1 & if\ FScore > {}^{3}/_{4} \\ k + 2 & if\ {}^{3}/_{4} \geq FScore > {}^{1}/_{2} \\ k - 2 & if\ {}^{2}/_{2} \geq FScore \geq {}^{1}/_{4} \\ \lceil (k/2) + 1 \rceil & otherwise \end{cases} \quad (1)$$

The optimal K-value determination algorithm ensures a lesser value with higher accuracy above 0.9. The succeeding phase calculates the number of clusters associated with an image. This will be a variable entity in FKISM for which the values differ based on the input image's pixel intensity variation. The entire image is processed during this phase to differentiate the area of interest from the usual texture surrounding the area. The images are operated in RGB 8-bit color space mode in FKISM. Thus, every individual channel of a pixel can have a value between 0 and 255 i.e. 2^8 for every channel.

The maximum number of permitted clusters n_c is calculated as $\frac{2^8}{k}$. Let δ be the segments set with themembers $\{\delta_1, \delta_2 \dots \delta_{n_c}\}$ where $n_c$denotes the maximum number of clusters is. Similarly, the segment intensity set λ is created by calculating the pixel intensity for every $\delta_x \in \delta$ using following equation and the segment intensity members are stored such as $\{\lambda_1, \lambda_2 \cdots \lambda_{n_c}\}$.

$$\forall i = k \rightarrow n_c\ in\ step\ k, \lambda_i = \left\lceil \frac{((i+1)\times k)-(i\times k)}{2} \right\rceil \quad (2)$$

The FKISM segmentation algorithm is given below

Algorithm 2: FKISM Image segmentation

Input: Retina Image

Output: Segmented Retina Image

Step 1: Let i_h be the height and i_w be the width of the input image

Step 2: $\forall i = 1 \rightarrow i_h :: \forall j = 1 \rightarrow i_w :=$

Step 3: $rgb = GetPixelValue(i, j)$

Step 4: $r = GetRedValue(rgb)$

Step 5: $g = GetGreenValue(rgb)$

Step 6: $b = GetBlueValue(rgb)$

Step 7: $a = \frac{r+g+b}{3}$

Step 8: $\forall l = 1 \rightarrow n_c := a' = \lambda_l\ if\ a \epsilon \delta_l$

Step 9: $rgb^{'} = (a^{'}, a^{'}, a^{'})$

Step 10: $PutPixel(i, j, rgb^{'})$

Step 11: end for step 2 loop

3.3 Feature Selection and Classification

After the image segmentation, the segmented data is fed into the AFSCNN for feature learning and classification. A CNN can process multi-dimensional data, including time series and image data. Its training phase performs feature extraction and weight computation for accurate detection. The main benefit of CNNs is that they offer automatic feature extraction. The feature learning of CNN comes with numerous pairs of convolutional as well as pooling layers. The convolution operation through digital filters is applied by the convolution layer on the input data. In addition to deciding the threshold, the pooling layer reduces dimensionality. Because backpropagation requires multiple parameter adjustments, the neural network architecture has fewer connections overall. The general architecture of CNN is given in Figure 2.

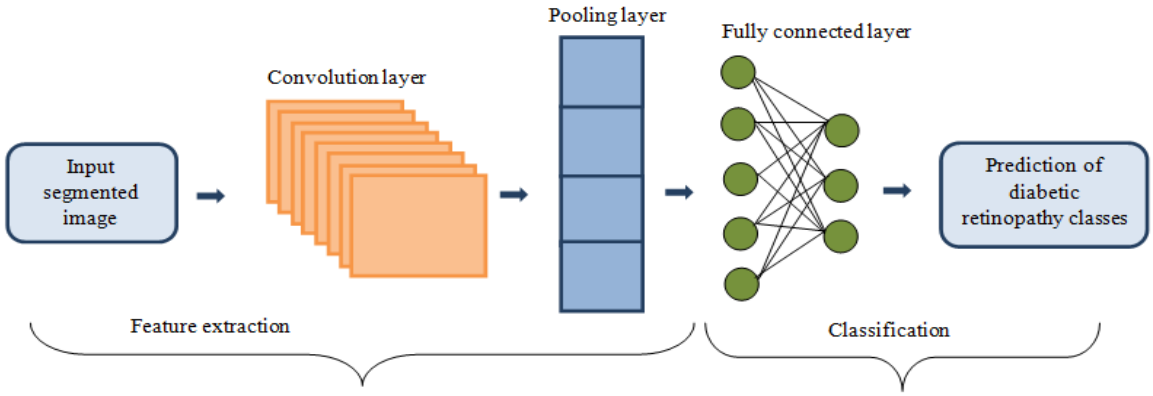


Figure 2: Structure of CNN

Initially, the AFSCNN used the PBD dataset to build the CNN kernels spontaneously with a set of 3x3 size filters. Every segmented image is loaded individually and scanned in raster format from left top to right bottom, as shown in Figure 3. Then the filter matrix set $f = \{f_1, f_2 \cdots f_{n_{max}}\}$ is stated with the following condition.

$$\forall i = 1 \rightarrow n_{max} := Add\ f_i\ to\ f\ if\ f_i \notin f \quad (3)$$

With this condition, the uniqueness of the new filter is ensured for each iteration, so that the maximum possible number of filters is $2^9 = 512$. The termination condition of this feature extraction process has multiple exit conditions to reduce the overrunning of the extraction process. The first one is when the number of filters n_{max} in set f equals to 512, and the second one is the image loading process reaches the end of PBD dataset.

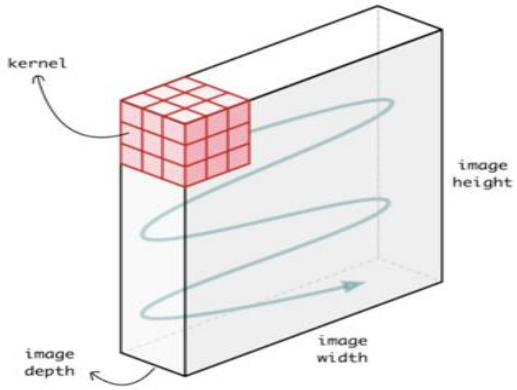


Figure 3: CNN raster scan direction

The feature selection process is performed by removing and computing the difference in F1-Score with and without a filter for every image. If there is no significant difference by removing a filter$f_x \epsilon f$, then it is removed from the feature set fAFSCNN filter selection algorithm is as follows

Algorithm: AFSCNN Filter selection
Input: PBD, filter ser$f$
Output: Beneficial Filter Set f_β

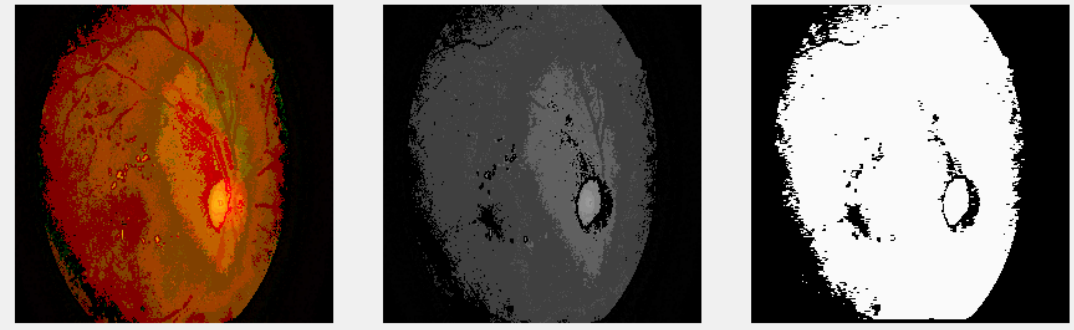
Step 1: Initialize $f_\beta = f$
Step 2: $\forall i = 1 \rightarrow \eta_{PBD} :: \forall j = 1 \rightarrow n_{max} :=$
Step 3: Compute F1-Score ε^+ with all features
Step 4: Compute F1-Score ε^- without feature f_j
Step 5: $Process = \begin{cases} Discard\ f_j\ if\ |\varepsilon^+ - \varepsilon^-| > 0.1 \\ retain\ f_j\ otherwise \end{cases}$
Step 6: End for Step 2 loop
Step 7: End for Step 1 loop
Step 8: return f_β

AFSCNN extracts all features and then eliminates those that do not provide a significant performance difference by comparing the F-Score indexes. The feature maps are down-sampled using pooling layers, which preserve the most critical data while reducing the spatial dimensions. The convolutional layers' output is passed via these layers. Once the pooling layers' output has been processed, the image is classified or predicted using one or more fully connected layers.

4. RESULTS AND DISCUSSION

Here, the results attained by the proposed and existing algorithms for DR detection from retinal fundus images are discussed. A computer with an 8th Generation Intel® Core™ i5-8250U Processor with a base frequency of 1.60GHz boosts up to 3.40GHz with Turbo Boost, 6MB Cache processor, 16GB Memory, and 1TB storage is used to perform the development and experiment processes. Visual Studio IDE [*1] creates a unique user interface to load the datasets and perform the evaluation process for every discussed method individually. C++ 20.0 [*2] programming language codes the proposed method algorithms.

The system collects the dataset from https://ieee-dataport.org/open-access/indian-diabetic-retinopathy-image-dataset-idrid for training and testing purposes. The training and testing ratios are set to 70:30, respectively. The dataset includes segmented, disease gradient, and localization images separately for training and testing purposes. The training is performed, and the data are logged for every 7% of data. Similarly, the testing process output data are logged for every 3% of data in report files and graphs. Figure 4 shows the outcomes of the proposed FKISM-based image segmentation system for segmenting the retinal lesions from the retinal fundus images.



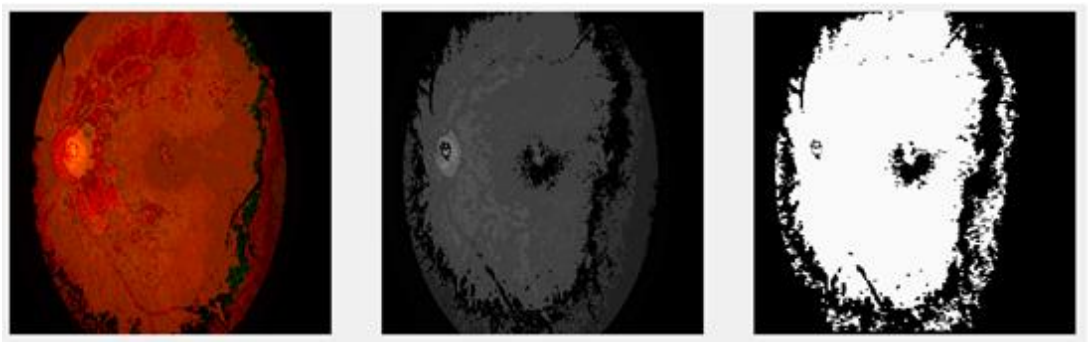


Figure 4: Sample images from the dataset and their corresponding greyscale and segmentation outcomes using FKISM

The existing methods taken for comparison are DRDL, HHODL, UDL, DLTF, and DRML, and these models are compared with our proposed system called k-nearest neighbour image segmentation-based convolution neural network (KCNN) regarding sensitivity, f-measure and accuracy. These measures are estimated based on four values such as true positive (Tp), true negative (Tn), false positive (Fp), and false negative (Fn) that are obtained for the actual as well as recognized samples of the classifiers. When the classifier correctly determines the positive class, the result is aTp. In the same way, Tn is the result when the classifier determines the negative class accurately. When the technique forecasts the positive class erroneously the result is called anFp, and when it estimates the negative class wrongly, the result is called aFn.

(a) Sensitivity

A classifier's sensitivity is the ratio of number of correctly classified positive instances and the total number of positive instances, which is computed as

$$\text{Sensitivity} = \frac{Tp}{(Fn+Tp)} \qquad (4)$$

(b) F-measure

It reflects the recall and precision's harmonic mean, and it is computed as follows:

$$\text{F-measure} = \frac{\text{Tp}}{\text{Tp}+1/2(\text{Fp}+\text{Fn})} \qquad (5)$$

(c) Accuracy

It is one of the most widely used indicators of classification performance as well as is calculated as the proportion of accurately categorized images to the total amount of images:

$$\text{Accuracy} = \frac{\text{Tp}}{\text{Tp}+\text{Tn}+\text{Fp}+\text{Fn}} \qquad (6)$$

Table 1 illustrates the outcomes of the proposed and existing schemes for training and testing data samples regarding sensitivity. The sensitivity of the techniques is plotted by varying every 10% of training (70%) and validation data (30%). The proposed KCNN gives the highest sensitivity of 97.98% in training and 97.88% in validation, higher than the existing techniques. The existing DRDL shows minimal outcomes, and the HHODL model shows the average outcomes compared to all other techniques. The UDL technique obtains outcomes similar to those of the proposed system; however, their results are lower than our proposed scheme's. It is clear from the table that our proposed system performs more remarkably than the existing DR detection techniques.

Table 1: Sensitivity of the proposed and existing systems

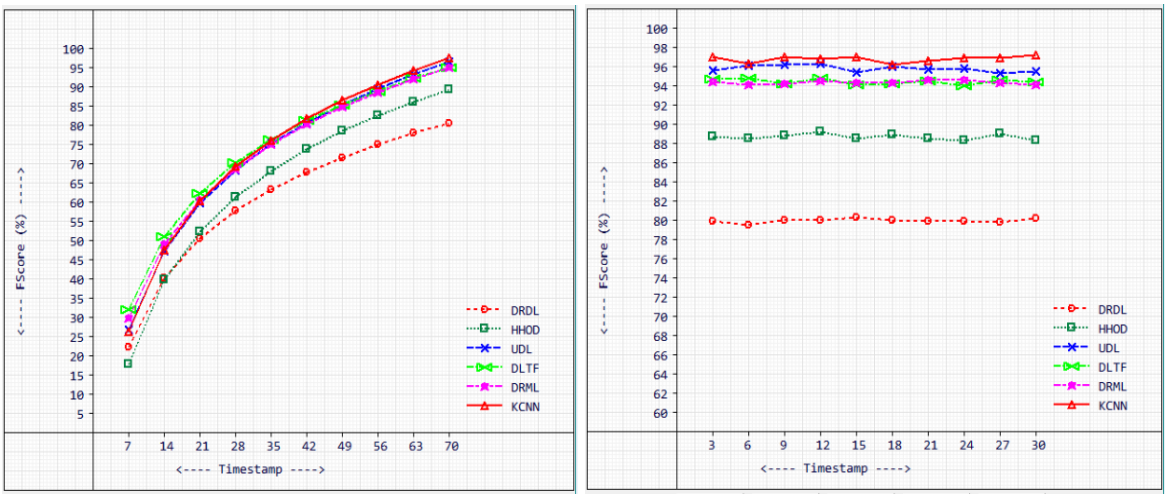
(a)

Data/Techniques	DRDL	HHODL	UDL	DLTF	DRML	KCNN
7	22.73	17.78	26.55	32.13	29.60	26.50
14	40.58	39.16	47.35	50.98	48.99	47.93
21	50.45	51.44	59.91	62.09	60.71	60.61
28	57.50	59.95	68.67	69.86	68.81	69.66
35	62.83	66.60	75.89	75.86	75.52	76.56
42	67.086	72	81.47	80.59	80.84	82.23
49	70.70	76.49	86.39	84.80	85.34	87.10
56	73.76	80.46	90.85	88.20	89.28	91.20
63	76.62	83.76	94.68	91.45	92.98	94.70
70	78.97	86.95	98.11	94.28	95.98	97.98

(b)

Data/Techniques	DRDL	HHODL	UDL	DLTF	DRML	KCNN
3	78.37	86.12	97.26	94.00	94.75	97.00
6	77.79	86.35	97.82	93.77	95.48	96.70
9	78.29	86.81	97.56	92.92	95.06	97.09
12	78.27	86.70	97.74	94.09	95.09	97.95
15	78.86	86.46	97.08	93.14	95.83	97.69
18	78.44	86.37	97.46	93.31	94.57	96.69
21	78.42	85.71	97.81	93.73	95.10	96.97
24	78.14	85.65	96.92	93.36	95.95	97.25
27	77.82	86.67	96.63	93.44	95.75	97.08
30	78.42	85.77	97.08	93.65	95.22	97.88

Figure 5 shows the training and validation f-measure obtained by the models for DR detection from retinal fundus data. The f-score of the techniques is plotted by varying every 10% of training (70%) and testing data (30%). It is observed from the figure that the proposed KCNN model attains a higher f-score than the existing models. When the data size increases, the f-score of the models is also increases. At the initial level, when the data size is 10% of the training (7), the proposed system attains the f-score of 26.36713, lower than DLTF, UDL, and DLTF. In contrast, the system attains the f-core of 97.578262 for 100% of the training data, which was higher than that of all other existing systems. Similar outcomes are obtained for the testing phase. Figure 6 shows the accuracy outcomes of the methods on training and testing.

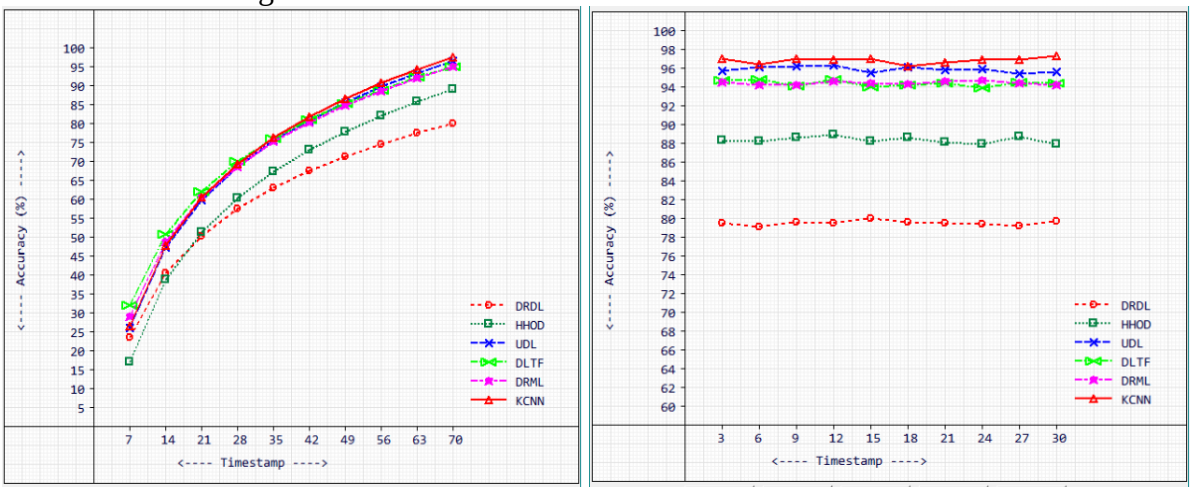


(a) (b)

Figure 5: Training and validation f-score of the classifiers

The accuracy of the techniques is plotted by varying every 10% of training (70%) and testing data (30%). It is observed from Figure 6 (a) that the proposed KCNN model attains higher accuracy than the existing techniques. When the data size increases, the accuracy of the models is also increased. For the 10% of the training data (7), the proposed system attains an accuracy of 26.73, whereas the existing DRDL, HHODL, UDL, DLTF, and DRML techniques give an accuracy of 23.61, 17.17, 26.05, 32.14, and 29.17. The accuracy of the techniques is increased when more data is used for training purposes.

In the end, the KCNN attained the maximum accuracy of 97.58% for 100% of the data samples used in training, which was better than the existing schemes. The existing UDL, DLTF, and DRML schemes proved their effectiveness in DR detection by achieving 96.64%, 95.08%, and 95.17% accuracies, which are higher than DRDL and HHODL. However, when comparing the training accuracies of the techniques for all data samples, the proposed KCNN provides superior outcomes compared to other existing techniques. Similarly, the proposed KCNN technique gives better outcomes for the validation data; it gives an accuracy of 97.315506, which is higher than that of other previous models. From the outcomes, we can conclude that the proposed KCNN more accurately detects the DR of the patients from fundus data than the existing schemes.



(a) (b)

Figure 6: Training and validation accuracy of the classifiers

5. CONCLUSION

DR is a significant blinding disease and one of the side effects of diabetes. The severity of DR lesions can be accurately diagnosed, which has significant clinical implications. Since early

detection can successfully prevent vision loss, early diagnosis and treatment are essential. Doctors can diagnose DR with greater accuracy and better patient outcomes when fundus images are automatically classified by DR. The current study aims to use an effective image segmentation technique along with a CNN to detect DR from fundus data earlier. The proposed system's outcomes are contrasted to the existing techniques regarding sensitivity, f-measure and accuracy under training and validation scenarios. The proposed technique offers a training accuracy of 97.58 that is comparatively higher compared to existing models. Similarly, the proposed system attains the best performance on training and testing compared to previous related schemes. In future, the work will be extended to analyze the DR patients' severity level with the help of a pre-trained CNN model.

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