Journal of Advances in Management, Engineering and Science (JAMES), 2025; 1(1): 19-26

Research Article

Diabetic Retinopathy Detection Using a Hybrid Deep Neural–Attention Mechanism Model

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Received 1st February 2025; Accepted 17th July 2025; https://doi.org/10.65470/james.2

Abstract **–** One common consequence of diabetes mellitus is DR, which destroys the retina and can cause permanent blindness if not caught in time. Treatment cannot undo DR, but catching it early and taking steps to prevent further vision loss can help keep eyesight intact. The necessity for trustworthy automated methods is highlighted by the fact that conventional diagnosis, which involves ophthalmologists utilising retinal fundus pictures, is time-consuming, expensive, and susceptible to human mistake. In this research, this survey current deep learning-based techniques for diabetic retinopathy detection and present DualAttTrans, a full-stack network that uses hybrid attention mechanisms to efficiently capture and analyse retinal image features on different scales and domains, without using additional priors or supervision. In order to get representative features for classification, the methodology begins with preprocessing to clean the data. Then, features are extracted. This is built a large-scale benchmark dataset with various retinal pictures at different DR severity levels to validate performance. The experimental results show that DualAttTrans outperforms the state-of-the-art methods with an impressive accuracy of 94.32%. The results show that DualAttTrans is an effective, efficient, and scalable technique for automated diabetic retinopathy detection; it can aid in early screening and protect at-risk patients' eyes from damage.

Keywords— *Diabetic Retinopathy (DR), Optical Coherence Tomography (OCT), Generative Adversarial Network(GAN).*

INTRODUCTION

Metabolic abnormalities brought on by insulin insufficiency or resistance characterize diabetes mellitus. Diabetic retinopathy, heart disease, kidney disease, and other complications are all possible outcomes of diabetes. DR is an eye disease that can lead to blindness if left untreated for an extended period of time. Effective treatment depending on severity can only be provided to patients if early detection is possible[1]. A leading cause of blindness in patients with diabetic retinopathy, a consequence of diabetes. The main cause of diabetic retinopathy is damage to the retina's blood vessels caused by high blood sugar levels. Particularly, the narrow and thin blood arteries become clogged when blood sugar levels are excessive[2]. Therefore, the retina does not receive any blood supply. The result is an effort by the body to create new blood vessels. Nevertheless, new blood vessels are fragile, that can lead to vascular ruptures. Unfortunately, new blood vessels aren't robust enough, so they burst. In the early stages of diabetic retinopathy, the patient may not have any symptoms at all.

Nevertheless, when DR symptoms worsen, they may involve: (i) blurred vision, (ii) a floating area or strip in the field of view, (iii) worsening eyesight, (iv) pain in the eyes, (v) problems with colors, and (vi) total blindness.

There are a number of restrictions despite the many approaches for DR detection and technological advancements. Due to the fact that conventional diagnosis methods rely heavily on the subjective, time-consuming, and costly manual examination of retinal pictures by qualified specialists. The screening

process is difficult in areas without easy access to specialist care, and its reliance on expert results makes it difficult to scale[3]. OCT and other retinal imaging tools are useful, but they can be uncomfortable and expensive for patients. As a result, it makes routine screenings less feasible. Diagnosis is already difficult enough without adding in the diversity in retinal image quality caused by variations in imaging equipment, lighting circumstances, and patient cooperation. This emphasized the need for sophisticated approaches that can process massive amounts of retinal pictures consistently and accurately, leading to an evolution in the demand for efficient, accessible, and automated DR detection solutions. On the other hand, OCTA allows for the visualization of the retinal microvasculature without the need of contrast agents, thus expanding the capabilities of traditional OCT[4]. In order to evaluate neovascularization, microaneurysms, and capillary non-perfusion, this method is highly beneficial. However, OCT continues to have more widespread adoption owing to its accessibility, quicker acquisition time, and capacity to detect early retinal oedema prior to the appearance of vascular abnormalities. Due to its accuracy, safety, and comprehensive structural assessment of the retina, OCT continues to be an essential tool for the early detection and monitoring of diabetic retinopathy, even though other imaging techniques are accessible for these purposes. Classical Euclidean geometry fails to adequately describe the human retinal vascular network due to its complicated branching structure, that is characterized by self-similarity and irregularities. Mathematically, fractal geometry provides a better way to describe these intricate biological structures. As vascular patterns are gradually altered in conditions like DR, fractal analysis has been beneficial in quantifying the global complexity of the retina's blood vessels.

Here is how the rest of the paper is structured. In Section 2, the Literature Review is detailed. Part 3 delves deeply into the SHNN architecture that has been suggested for evaluating groundwater quality with few shots. The verification of the result and discussion is the focus of Section 4. Section 5 concludes with some thoughts on where to go from here.

LITERATURE SURVEY

In order to detect DR in retinal fundus images early on, they developed a novel automated approach. Principal component analysis was used to extract rich feature values from the obtained raw images after they had been normalized using the typical scalar approach. In addition, DNN was fed the best feature values acquired after feature dimensionality reduction using the firefly technique[5]. In terms of statistical analysis demonstrates that the created model is the best in DR detection. In order to get good results in DR detection, they normalized the images and improved the retinal architecture[6]. Using the data, they created a DL algorithm to classify diabetes. To extract dynamic features associated to the data, a combination of LSTM and convolutional neural networks was utilized. When applied to the dataset, the model's predictions for spot diabetes are very accurate. They detailed a method that combined deep learning with image processing to identify and categories DR[7]. Machine learning algorithms also include naive bayes. Naive Bayes is a method for classifying data that differs from others in that it relies on probability theory. Numerous domains have made extensive use of naive bayes due to its simplicity and efficiency; they include the identification of cardiovascular disease risk levels, the diagnosis of Parkinson's illness, the management of glaucoma, and biomarker selection and categorization using the data[8]. Furthermore, in the early stages of DR, symptoms such as microaneurysms, cotton versions, and retinal hard exudates are uncommon and difficult to detect under the microscope[9]. A missed opportunity to halt progression may occur for certain patients due to a misdiagnosis. Nevertheless, it is well-known that DR can be halted with early laser photocoagulation treatment.

In order to diagnose the severity and degree of the disease at an early stage, they suggested blood vessel segmentation processes using a MLP neural network. They also intended to use a unique combination of classifiers, such as a SVM and a GMM[10]. They

used an ANN to calculate the ex-classification based on many features such size, shape, color, and texture in order to identify the DR in the background photos[11]. Their segmentation method was based on an innovative unsupervised learning mechanism that was based on the ant colony optimization method. Retinal pictures contain intricate linkages, and GNNs provide a new way to organize these interactions[12]. GNNs use a graph representation for images, with nodes representing image regions and edges representing the connections between them. In order to accurately identify DR, GNNs rely on this structure to capture the spatial and structural interactions among various retinal components. Investigating GNNs for DR detection has recently yielded promising results, showing that these networks may efficiently shape the retinal vasculature and detect irregularities due to DR[13]. In order to better detect microaneurysms and hemorrhages, for example, they built a GNN-based structure that used the structural information encoded in the retinal graphs. Finding an appropriate, and frequently non-sparce, reward function to accelerate the model's convergence towards the target policy is known as reward shaping[14]. Showing the intended behavior or imitating it is a common way to deduce this. However, the processing resources required by RL are further intensified by Invers Reinforcement Learning, an extension of the RL framework that can help infer an optimal reward function from a desirable conduct and shape the rewards favorably.

The following is an overview of our overall contributions:

- Adaptive Local Hybrid Domain and Adaptive Global DualAttTrans are two new hybrid attention mechanisms that they provide in the DualAttTrans, an end-to-end spectral highlight elimination network. By utilising these attention mechanisms, DHAN-SHR is able to efficiently and effectively remove Diabetic Retinopathy Detection while maintaining underlying diffuse components by capturing spatial and spectral information and contextual correlations at different scales.
- Extensive experimental evidence shows that DualAttTrans is superior to current approaches, establishing a new benchmark for image enhancement and diabetic retinopathy detection.

PROPOSED SYSTEM

When diabetes causes damage to the retina, it is called DR. Diabetic eye disease is another name for this condition. It may cause blindness in the long run. Diabetic eye disease manifests itself visually. Despite these frightening numbers, studies show that with adequate and careful eye care, at least 90% of these new instances may be decreased. Risk of developing diabetic retinopathy increases with duration of diabetes. Problems with delayed results, miscommunication, and postponed treatment arise when human reviewers take their time to provide their evaluations which can be up to two days after the first request.

These pictures are retina scans that can identify diabetic retinopathy. At APTOS 2019 Blindness Detection, you may find the original dataset. In order to make them compatible with a wide variety of pre-trained deep learning models, these photos are downsized to 224x224 pixels. Every single photograph has already been saved in its own folder based on the degree and stage of diabetic retinopathy detected by the train. the supplied csv file[15].

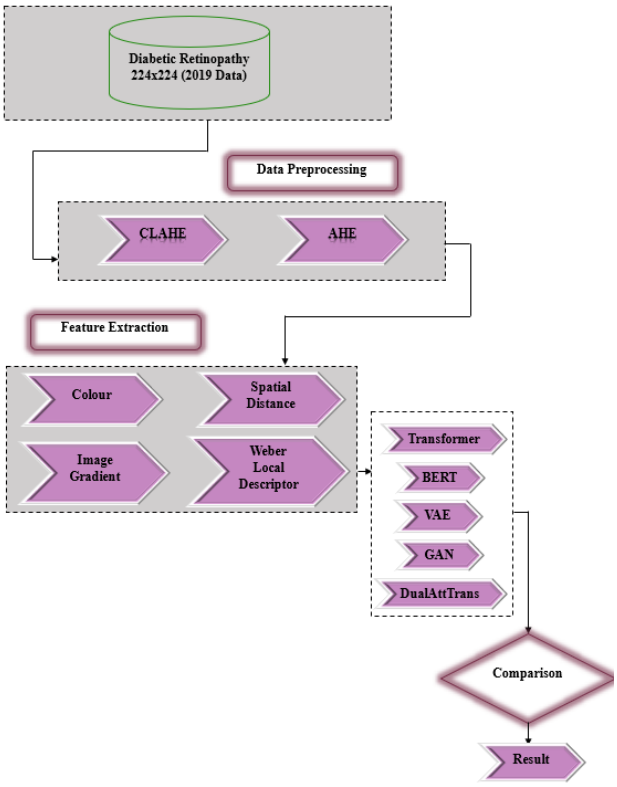

Fig. 1.Block Diagram Of Proposed Method

Figure 1 shows a pipeline that the high-level process relies on, highlighting the significance of this approach. In our research found the best performing model by experimenting with three pre-trained models on the raw retinal fundus dataset. They trained this dataset using the top performing model from the prior experiment, and then applied typical image processing algorithms to our raw fundus images. They additionally used DualAttTrans architecture to train preprocessed images from the ground up. On the last step, researchers compared the outcomes to see if the models' performance accuracy was enhanced by using preprocessed photos.

A. Data Preprocessing:

Images were pre-processed using image enhancing techniques, including popular ones like contrast enhancement and lighting correction, to improve their look and information value. Image visibility is improved by the use of CLAHE. The AHE procedure includes CLAHE as an adjusted component. By applying the boosting function to all nearby pixels, this technique derives the transformation function. This differs from AHE due to the lack of contrast. Instead of applying CLHE to the whole image, CLAHE applies it to smaller data regions termed tiles in order to improve the image's contrast. The next step is to use bilinear interpolation to precisely sew back the adjacent tiles. Greyscale retinal images were subjected to CLAHE[16]. To reduce image noise, the cliplimit function is used. Make a histogram clip and a grey level map. The average number of grey pixels in the contextual region is calculated by dividing the pixel numbers evenly for each grey level, as shown in equation (1).

$$m_{avg} = \frac{m_{DQ-w_o} * m_{DQ-z_o}}{m_{gray}} \quad (1)$$

Where, $m_{avg} = average\ pixel\ count$, $m_{gray} = count\ of\ contextual\ grey\ levels$

m_{DQ-w_o} =pixels along the w-axis of the contextual area

m_{DQ-z_o} = count of contextual region's z-axis pixels Next, determine the true cliplimit in equation (2).

$$m_{DK} = m_{CLIP} * m_{avg} \quad (2)$$

Because it effectively makes the typically significant salient parts more accessible, CLAHE is a helpful technique in biomedical image processing. Fixing the lighting uneven lighting of retinal pictures causes the scenario effect, which this preprocessing method attempts to mitigate. Equation (3) is used to determine the intensity of each pixel.

$$o' = o + \delta_C - \delta_K \quad (3)$$

In this case, C stands for the target average intensity and K for the local average, while o & o' denote the starting and ending values of the pixel sizes, respectively. This approach improves the diagnosis of microaneurysms developing on the retina's surface.

B. Feature Extraction:

Colour difference dc: It is determined by referring to equation (4).

$$c_d = \sqrt{\left(\frac{\Delta k}{l_k t_k}\right)^2 + \left(\frac{\Delta d}{l_d t_d}\right)^2 + \left(\frac{\Delta g}{l_g t_g}\right)^2}, \ldots \quad (4)$$

where $\Delta k, \Delta d, \Delta g$ stand for the corresponding disparities between any two pixels.

- **Significance:** Each pixel's contrast is determined by its colour difference.

Spatial distance:

- **Significance:** In three-dimensional space, the length of a straight line can be determined by calculating the spatial distance between any two pixels.

Image gradient:

- **Significance:** A retinal picture's changes in directional intensity can be discovered with the help of an image gradient[17].

Weber local descriptor:

- **Significance:** The features are located by analysing patterns and differences in texture using the Weber local descriptor.

To see the distance C between pixels, look at equation (5).

$$C = \sqrt{\omega_d(c_d)^2 + \omega_t(c_t)^2 + \omega_h(c_h)^2 + \omega_v(c_v)^2}, \ldots \quad (5)$$

C. Model Training:

1) Adaptive Global Dual Attention Transformer (G-DAT):

At the point where the encoder and decoder are slowed down, G-DAT are used. The information carried by each pixel is more abstract and globally contextualised at this step due to the higher semantic level compared to any other layer in the network. This increased degree of abstraction prompted us to develop simultaneous dual attention methods. These are made to simultaneously understand the complex global inter-channel and inter-pixel relationships, as shown in equation (6).

$$G - DAT(\hat{E}) = \gamma \times CCAT(\hat{E}) + (1-\gamma) \times PSAT(\hat{E}) \quad (6)$$

The fact that each feature map $\hat{E}$ is significantly smaller after going through numerous down sampling steps means that not even the PSAT, which focusses attention globally, places a heavy computational burden on the system. DualAttTrans is shown in Algorithm 1.

Algorithm 1: Algorithm for DualAttTrans	
Require: F($input\ features$)	
Ensure: $F_t(frequency\ processed\ features)$	
1.	Apply convolution: $identity_1 \leftarrow Conv2d_{1\times1}(F)$
2.	Apply convolution: $identity_2 \leftarrow Conv2d_{1\times1}(F)$
3.	Calculate the FFT of F and retain the real component: $F_{fft} \leftarrow FFT(F, dim = (-2,-1)).real$
4.	Apply convolution to F_{fft}: $F_{fft} \leftarrow GELU(Conv2d_{1\times1})(F_{fft}))$
5.	Pass through MLP layers: $F_{fft} \leftarrow MLPs(F_{fft})$
6.	Compute inverse FFT: $F_{ifft} \leftarrow IFFT(F_{fft}, dim = (-2,-1)).real$
7.	Add residual connection: $F_t \leftarrow F_{ifft} + identity_2$
8.	Apply toning: $F_t \leftarrow Toning(Concat([F_t, identity_1], dim = 1))$

In biomedical image processing, CLAHE is a helpful technique since it effectively increases accessibility to the typically significant prominent areas. Furthermore, spectral domain elements are not included in PSAT since the input to the bottleneck module is devoid of some visual information. This method maintains linear computing efficiency by guaranteeing that the computational requirement is exactly proportionate to the spatial dimensions of each feature map[18].

2) Objective Function:

Our objective is to improve the performance of our Diabetic Retinopathy Detection approach by ensuring that the output closely matches the ground truth diffuse images. Accomplishing this requires not only preserving but also reaching pixel-level accuracy. They do this by introducing a composite objective function that combines two metrics: Mean Squared Error Loss L_e which measures fidelity at the pixel level, and Structural Similarity Loss L_t which focusses on preserving structural integrity. The

following is the form of our overarching objective function shown in equation (7).

$$L = x_1.L_e + x_2 + L_t \quad (7)$$

where $x_1 is\ equal\ to\ x_2$ is equal $1\ to\ 0.4$, as determined empirically. As shown in equation (8), then apply the suggested SSIM to our target function's structural similarity component L_t.

$$L_t = 1 - \frac{(2\delta_C\delta_H + D_1)(2\sigma_{CH} + D_2)}{(\delta_C^2 + \delta_H^2 + D_1)(\sigma_C^2 + \sigma_H^2 + \sigma_2)} \quad (8)$$

In this context, $\delta_C \& \delta_H$ stand for the average pixel values of the output diffuse picture C and the target ground truth image G, respectively. $\sigma_C^2 \& \sigma_H^2$ are the variances of these two images, and σ_{CH} is the covariance between $D_1 \& D_2$ which are constants used to stabilise the division with weak denominators.

RESULT AND DISCUSSION

One of the many complications of diabetes, DR affects people all over the globe. Retinal microvasculature changes bring about DR as a result of an elevated blood glucose ratio. Total blindness results from DR even in the absence of warning signs. In spite of this, the incidence of DR can be managed with early screening with CAD techniques and appropriate therapy. It is a difficult and time-consuming process to manually examine the retina for morphological alterations. The need for ophthalmologists to be able to observe both inter- and intra-variations led to the development of numerous CAD systems in the past. Figure 2 displays the DualAttTrans model's loss curve over the course of the training epochs. Initially, the training loss is somewhat significant at around 93%, but it decreases gradually over the epochs, reaching a low of approximately 24% by the 100th epoch.

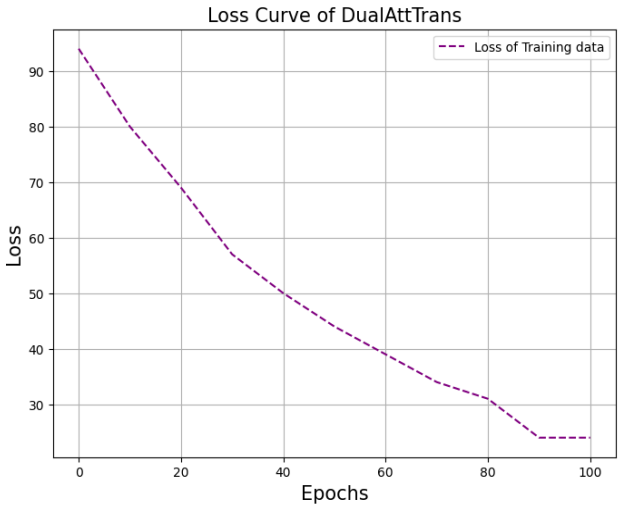

Fig. 2.Loss Curve of DualAttTrans

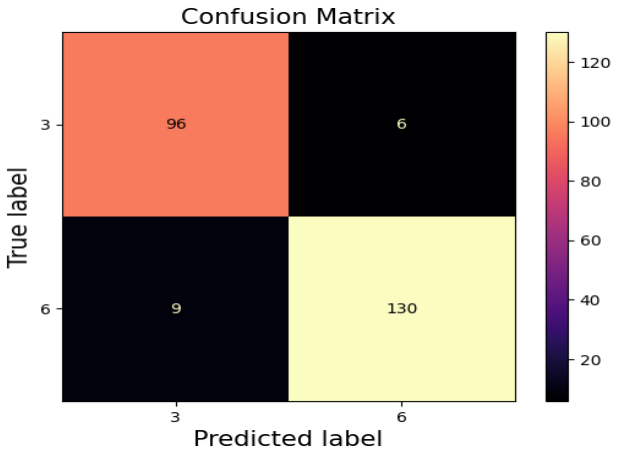

Fig. 3.Confusion Matrix

Figure 3 shows the confusion matrix measures a model's ability to classify 3 and 6 items. Class 3 was properly identified in 96 of the three samples from each class, while 6 were incorrect. The true class 6 had 130 correct predictions, however 9 were misclassified as class 3.

TABLE I. PERFORMANCE ANALYSIS

Models	**Accuracy**	**F1-Score**	**SEN**	**SPE**
Transformer	89.43	89.69	88.96	90.89
BERT	85.29	85.82	84.69	86.96
VAE	90.16	90.79	89.81	91.72
GAN	87.38	87.63	86.74	88.82
DualAttTrans	**94.32**	**94.98**	**93.63**	**95.79**

Transformer, BERT, VAE, GAN, and DualAttTrans are among the five models whose performance is examined in Table 1. The accuracy, f1-Score, SEN, and SPE of our suggested DualAttTrans model are all above average, coming in at 94.32%, 94.98%, 93.63%, and 95.79%, respectively.

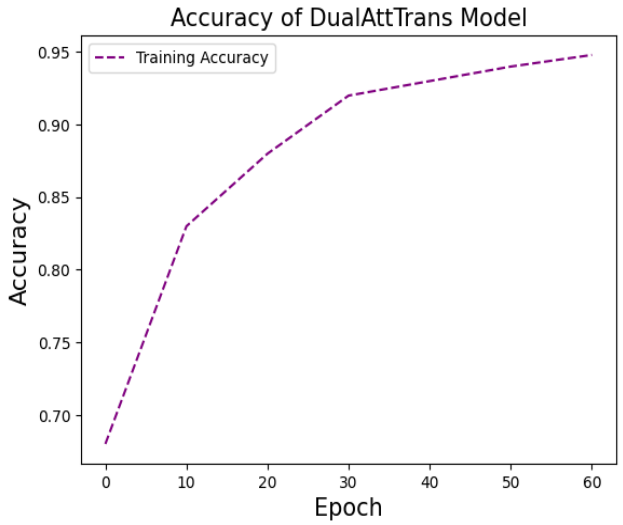

Fig. 4. Accuracy of DualAttTrans Model

The accuracy of the DualAttTrans Model is displayed in Figure 4 for various time points. Starting at around 0.68 in the first epoch and reaching around 0.95 in the 60th epoch, the training accuracy steadily increases.

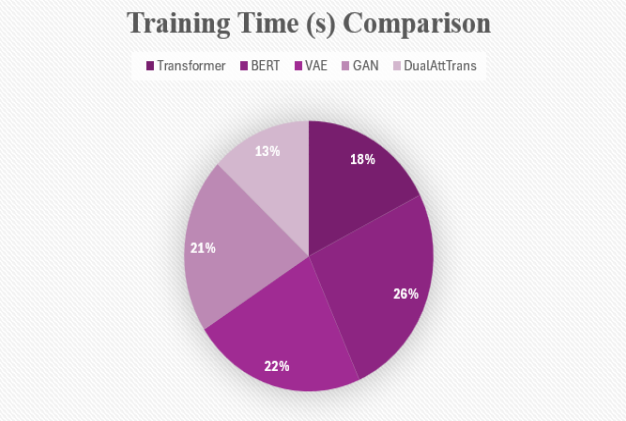

Fig. 5. Training Time Comparison

Figure 5 shows that the following networks require different amounts of time to train: VAE (22%), GAN (21%), Transformer (18%), and DualAttTrans (13%). According to the figure, DualAttTrans is the most effective model, whereas BERT requires the most time for training.

CONCLUSION

One of the most serious consequences of diabetes, DR can cause permanent blindness if not caught in time. Millions of people may reap the benefits of faster diagnoses with fewer mistakes if this detecting stage were automated. There have been a number of deep learning models used for DR detection, however the expensive expense of collecting huge labelled datasets and inconsistent annotations have severely hindered their effectiveness. In response to these difficulties, they provide DualAttTrans for Diabetic Retinopathy Detection, a full-stack network that doesn't need any extra priors or supervision to capture global and local dependencies across domains and sizes. The model is able to accurately mimic intricate relationships seen in retinal images because the procedure incorporates pretreatment for picture cleaning, feature extraction, and incorporation of spectral domain characteristics. To test the method, they created a massive benchmark dataset including pictures from different DR steps. By surpassing previous models, DualAttTrans attains a classification accuracy of 94.32%, according to experimental results. Improved therapeutic results and more research are possible outcomes of these findings, which show its promise as a scalable, efficient, and dependable technique for early DR identification.

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