**A dual-branch CNN network for** **Multi-Class Classification Model for Eye Disease Detection**

**Abstract**

Herein, we introduce a new method for the classification of fundus images using a parallel dual-branch CNN-Trans model. The model architecture is a combination of Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Vision Transformers (ViT), and Coordinate Attention mechanisms to improve fundus image classification accuracy. The model is engineered to process and classify retinal fundus images into several categories using the strengths of both feature extraction and sequential learning. The CNN branch is used to extract spatial features from the images, while the LSTM branch is used to extract sequential dependencies in the data. The ViT and Attention branches are utilized to obtain global context and increase the spatial awareness of the network. The model is trained and tested based on a 90% training, 5% validation, and 5% testing split, with performance metrics measured through accuracy, precision, recall, F1-score, and confusion matrix. Our findings show that the proposed model can perform effectively in classifying fundus images with better performance than conventional methods with high accuracy and resistance in retinal disease detection in various classes of fundus data.

**Keywords:**

Fundus Image Classification, CNN-Trans Model, Dual-Branch Network, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Vision Transformer (ViT), Coordinate Attention, Retinal Image Processing, Deep Learning, Image Classification, Precision, Recall, F1-Score, Confusion Matrix, Multi-Branch Network, Medical Imaging, Fundus Photography

1. **INTRODUCTION**

Retinal diseases like diabetic retinopathy, glaucoma, macular degeneration, and retinopathy of prematurity are the top causes of blindness and visual impairment globally. Proper diagnosis and early detection of such conditions are crucial for preventing loss of vision as well as proper treatment. Diagnosis of most ocular diseases depends on the analysis of fundus images that have been obtained via fundus photography. Yet, fundus image analysis manually is a time-consuming and expert-based procedure, which frequently results in inconsistency and delay in diagnosis.

Recently made progress in deep learning, notably Convolutional Neural Networks (CNNs), has transformed medical image analysis such as fundus image classification. Although CNNs have proved with great success on extracting features from images, generally they are most successful at preserving local patterns yet may not appreciate long-range dependences and worldwide context, where often these could be the pivotal points in the medical images. Also, sequential data or contextual relationships in retinal images can be important for correct diagnosis, but such dependencies are usually neglected by conventional CNN-based models.

In response to these deficiencies, this paper introduces a new architecture, which is CNN-Trans, parallel dual-branch network tailored particularly for fundus image classification. The CNN-Trans model integrates CNNs, Long Short-Term Memory networks, Vision Transformers, and Coordinate Attention mechanisms under one framework. Each of the network branches is specifically designed to extract various feature types: local features are extracted by the CNN branch, sequential dependencies are processed by the LSTM branch, global context is extracted by the ViT branch, and spatially important regions are attended to by the Coordinate Attention branch. This multi-branch design aims to take advantage of the individual performance of each single model and build a more extensive representation of the fundus image and better classification performance.

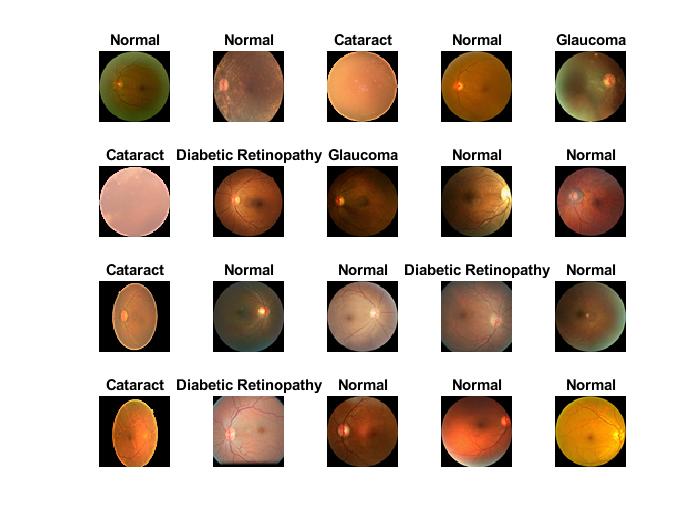


Fig1. Fundus Images

In response to these deficiencies, this paper introduces a new architecture, which is CNN-Trans, parallel dual-branch network tailored particularly for fundus image classification. The CNN-Trans model integrates CNNs, Long Short-Term Memory networks, Vision Transformers, and Coordinate Attention mechanisms under one framework. Each of the network branches is specifically designed to extract various feature types: local features are extracted by the CNN branch, sequential dependencies are processed by the LSTM branch, global context is extracted by the ViT branch, and spatially important regions are attended to by the Coordinate Attention branch. This multi-branch design aims to take advantage of the individual performance of each single model and build a more extensive representation of the fundus image and better classification performance.

The CNN-Trans model is intended to improve the accuracy and reliability of fundus image classification to enable more efficient and accurate early diagnosis of retinal disease. Through blending the strengths of different deep learning methods, this work attempts to promote the state-of-the-art in retinal image analysis and provide a promising tool for automatic disease detection in ophthalmic clinical practice.

1. **RELATED WORK**

Fundus image classification has attracted much interest in the medical imaging community, with many studies emphasizing the development of automated systems for the detection of retinal disease. Conventional methods tend to use hand-engineered features and machine learning classifiers; however, with the emergence of deep learning, particularly Convolutional Neural Networks (CNNs), great strides have been achieved in the automation of retinal image analysis. Early research in this area mainly utilized CNNs for classification purposes, with most studies demonstrating impressive accuracy in detecting conditions like diabetic retinopathy and age-related macular degeneration (AMD) [1]. These CNN-based systems can learn hierarchical features from raw pixel data and outperform the traditional handcrafted feature-based methods by a significant margin.

Gulshan et al. [2] developed a deep learning architecture that employed a CNN for the diagnosis of diabetic retinopathy (DR). Their study showcased the capability of CNNs in producing human-level accuracy for the diagnosis of diabetic retinopathy, and they pointed out the possibility of using deep learning for large-scale screening schemes. Likewise, Rajalakshmi et al. [3] employed a CNN-based model for diabetic retinopathy classification in retinal fundus images, which demonstrated an improvement in diagnostic performance over conventional methods. These methods were mostly concerned with local feature extraction but did not account for the global relationships and contextual information that can be present among various regions of the retina.

By comparison, Vision Transformer (ViT) methods have been brought to the foreground as they tend to capture longer-range dependencies across images, in which CNNs could fail on account of limited receptive fields. ViTs deal with image patches as sequences and leverage self-attention mechanisms in modelling global contexts. Chen et al. [4] showed the effectiveness of ViTs in medical image analysis, as they proved the transformer architecture superior to CNNs in some applications such as detecting lung disease. Wu et al. [5] investigated the integration of CNNs with LSTMs for medical image classification, demonstrating that LSTMs were able to encode contextual information in images, beneficial for applications such as detecting diabetic retinopathy from a sequence of retinal scans. Although LSTMs have indicated potential in sequence tasks, the use of these in fundus image analysis is limited, particularly when dealing with intricate, high-dimensional data such as retinal images.

Recent developments have also integrated Attention mechanisms, specifically the Coordinate Attention mechanism, to enhance feature extraction and enhance the spatial attention of the model. The study by Hou et al. [6] brought forth coordinate attention for image classification, having shown that incorporating attention along the spatial directions can result in better performance through attending to appropriate regions of the image, which is very important in medical image tasks where particular areas, like the optic disc or macula, are central to diagnosis.

Apart from the initial achievements of CNNs and their combination with other models, more recent work has also pursued and enhanced fundus image classification by using hybrid models that seek to improve feature extraction, processing, and classification performance. Other research has also addressed the problem of class imbalance, where some retinal conditions are underrepresented in datasets, and suggested ways to solve the issue.

Hybrid CNN-RNN Architectures have been investigated to enhance the identification of intricate, sequential information in medical images. For instance, Bai et al. [7] introduced a hybrid deep model integrating CNNs and Recurrent Neural Networks (RNNs), where CNNs were employed to identify local image features, while the RNNs, namely the LSTM component, captured temporal patterns in the data. This hybrid model has been effective in applications such as multi-frame retinal imaging, where knowing the temporal relation among images can be helpful for better diagnosis. Liu et al. [8] also developed a hybrid CNN-LSTM architecture solely for the task of diabetic retinopathy classification, in which CNN drew the spatial features, and the LSTM network to model global trends in the sequence of images.

One of the promising avenues in fundus image classification is the application of Generative Adversarial Networks (GANs) for data augmentation and feature learning enhancement. He et al. [9] utilized GANs to create synthetic fundus images for training deep learning models to overcome the challenge of scarce annotated medical images. GANs have also been used to enhance the diversity of training data, and this improves the ability of the model to generalize, particularly in cases where there is limited data. In addition, GANs can be utilized adversarial, such that they improve the robustness of a model by training the model to be immune to adversarial attacks, enhancing the capability of the model to process real-world noisy fundus images.

Attention Mechanisms have also been considered as a method to enhance model performance through attending to the areas of greatest interest on the fundus image. Wang et al. [10] proposed a CNN with spatial attention mechanism that put more emphasis on critical regions like macula or optic disc, in which diabetic retinopathy tends to appear. Their method presented better results for diabetic retinopathy early detection. In addition, Zhang et al. [11] introduced an attention-based CNN model for retinal image analysis in which they utilized both spatial and channel attention mechanisms. The attention layers enabled the model to pay attention to the most informative features, which significantly enhanced classification accuracy, especially in the detection of subtle pathologies such as microaneurysms or haemorrhages.

The U-Net architecture, which proved to be effective in medical image segmentation tasks, has also been applied to fundus image classification. Isensee et al. [12] proposed an adapted version of U-Net for fundus image segmentation and classification, where CNNs are coupled with advanced segmentation methods for the extraction of more detailed features. This methodology has been most beneficial in automatically segmenting the retina, isolating areas of interest for the diagnosis of disease, enhancing accuracy in the classification of diseases such as glaucoma and age-related macular degeneration (AMD). Besides architectural innovations, utilization of multi-modal datasets has also been a new trend. Kermany et al. [13] demonstrated that integrating disparate imaging modalities like optical coherence tomography (OCT) and fundus photography within a multi-modal deep learning system enhances the detection and classification of a range of retinal pathologies. Such multi-modal systems attempt to integrate the complementary strengths of disparate imaging methods so that they can perform a more robust and inclusive analysis of retinal pathologies.

Lastly, Transfer Learning has become increasingly popular to address the problem of scarce annotated data in medical imaging. Tajbakhsh et al. [14] investigated the application of transfer learning for retinal image classification, where pre-trained models such as VGG16, ResNet, and Inception were fine-tuned on fundus images. This method showed better performance on small datasets, allowing models to utilize previously acquired features from large-scale natural image datasets and transfer them to medical imaging tasks. In short, though deep learning models, particularly CNNs, have shown significant success in classifying fundus images, difficulties are still present in retaining both local and global context and temporal and spatial relationships in retinal images. The integration of CNNs, LSTMs, ViTs, and attention mechanisms, as in this paper, tries to overcome these difficulties by capitalizing on the merits of each method towards more accurate and robust retinal disease classification.

1. **PROPOSED METHODOLOGY**

**CNN-Trans Model for Classification of Fundus Images**

The methodology to be used in the proposed system is a two-branch architecture for fundus image classification using Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Vision Transformers (ViT), and Coordinate Attention mechanisms. The use of a multi-branch architecture helps in extracting both local and global features from the fundus images, thus enhancing the classification accuracy. We discuss the operation of both branches of the network below in detail, highlighting their layers, functions, and roles.

The suggested CNN-Trans fundus image classification model adopts a multi-branch structure that comprehensively integrates local, sequential, global, and attention-based characteristics to enhance the classification accuracy. The block structure of the model is composed of multiple major blocks divided into specific branches. The input layer captures the fundus image, and the image is subsequently passed into four parallel branches: the CNN branch, the LSTM branch, the ViT branch, and the Coordinate Attention branch.

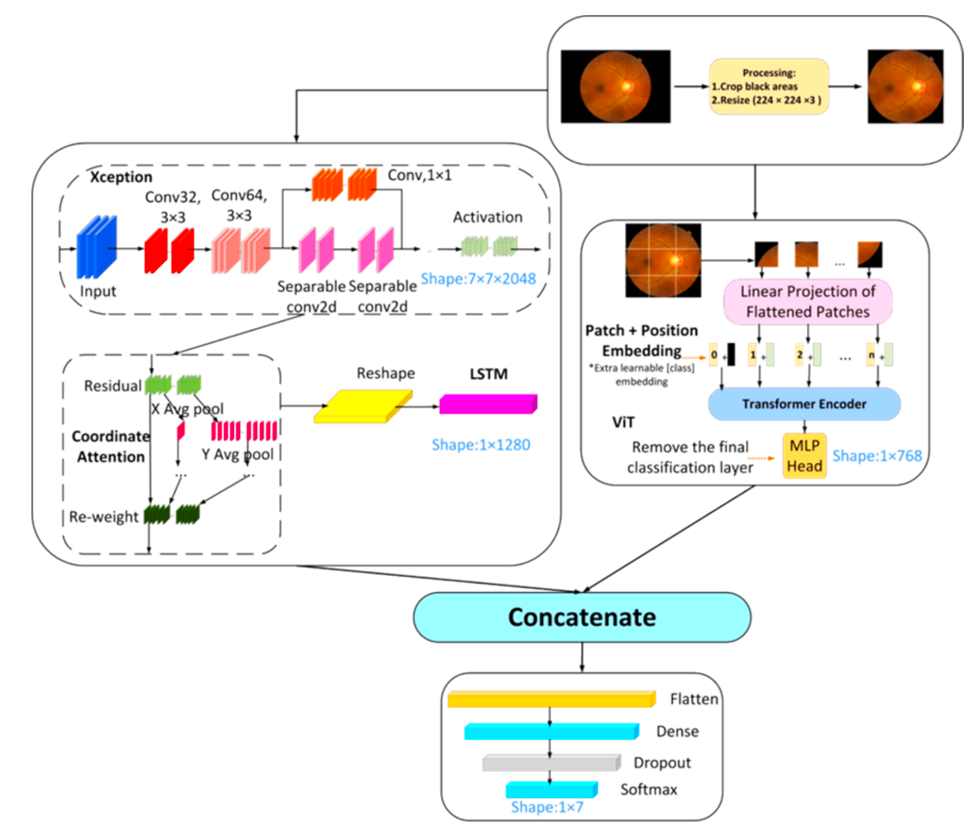


Fig1. Proposed Architecture

**1. CNN Branch:** This branch extracts the local features from the image. It begins with a convolutional layer where the filters are applied to the image to find elementary patterns like edges and textures. The result is normalized by a batch normalization layer, followed by a ReLU activation function and a max-pooling layer to reduce spatial features down to the most relevant ones.

**2. LSTM Branch:** The second branch starts with a convolutional layer that learns higher-level features, then batch normalization and ReLU activation. Following the convolution operations, the output is flattened and fed to an LSTM layer, which learns sequential dependencies and contextual information through the image. This process aids in comprehending relationships among various regions of the retina.

**3. ViT Branch:** This branch utilizes a fully connected layer to change the feature map from the CNN branch, which is then flattened. The Vision Transformer (ViT) then employs a self-attention process to learn long-distance dependencies within the image so that the model has access to global contextual information, which could prove vital for the classification of the disease.

**4. Coordinate Attention Branch:** Like the ViT branch, this branch uses a fully connected layer on the feature map of the CNN branch followed by flattening. The coordinate attention mechanism refines spatial attention so that the model can pay attention to important areas of the image that are critical for classification, making the model more sensitive to fine features.

After processing the input image, all four branches' outputs are concatenated into one vector and fed into fully connected layers. The last fully connected layer produces 7 output classes for various retinal diseases. The output is processed through a softmax layer to transform the output into probabilities, where the highest probability is assigned to the predicted class. The model applies a classification layer to make the final prediction. The overall network is trained to maximize performance by learning weights from a training dataset and tested using accuracy, precision, recall, and F1-score metrics.

The major benefit of this multi-branch structure is that it takes the best from each branch: the CNN extracts local features, LSTM handles sequential data, ViT extracts global context, and Coordinate Attention refines the attention on critical regions in the image. This synergistic mechanism enables the model to better classify fundus images, particularly with complicated patterns and subtle details in retinal images.

**1. Network Architecture Overview**

The network has four primary branches:

**CNN Branch:** Exports local spatial features from the image.

**LSTM Branch:** Represents sequential dependencies or context relations in the image.

**ViT (Vision Transformer) Branch:** Represents global context through learning attention-based features.

**Coordinate Attention Branch:** Exports to enhance attention mechanism, raising spatial awareness. These branches are concatenated and then a fully connected (FC) layer is applied for final classification.

**2. CNN Branch (Convolutional Neural Network)**

**Convolutional Layer (conv1):** The initial layer convolves the input image with a 3x3 kernel and 32 filters. The primary intention of this layer is to extract primitive features from the input image, including edges, textures, and patterns. The padding is defined as "same" to maintain the spatial dimensions of the input image. It extracts local patterns and spatial hierarchies in the image, which are critical in discriminating among various fundus image categories.

**Batch Normalization Layer (bn1):** It normalizes the activations of the former layer to speed up training and enhance network stability.

**Role:** Prevents internal covariate shift, enhancing the general training process.

**ReLU Layer (relu1):** The ReLU activation function brings non-linearity into the network, allowing the model to learn complex feature relationships.

**Role:** Non-linear transformation to enable the network to learn complex representations.

**Max Pooling Layer (maxpool1):** Does max pooling with a filter size of 2x2, decreasing the spatial size of the image and keeping only the significant features.

ROLE: Down sampling of the feature maps decreases computation but maintains significant spatial features. The CNN branch extracts local features from the input image. The branch is efficient in extracting fine-grained patterns like textures and edges, which are crucial for identifying various classes of retinal diseases.

**3. LSTM Branch (Long Short-Term Memory)**

**Convolutional Layer (conv2):** The second convolutional layer has a 3x3 convolution with 64 filters. This layer extracts more complex features than the CNN branch. Extracts features at higher levels following the first feature extraction by the CNN layer.

**Batch Normalization Layer (bn2):** Same as the CNN branch, batch normalization is used to maintain stable learning.

**ReLU Layer (relu2):** Adds non-linearity to the convolutional layer's output.

**Max Pooling Layer (maxpool2):** Same as the CNN branch, this layer downscales spatial dimensions and preserves essential features.

**Flatten Layer (flatten1):** Transforms the 2D output from the convolutional layers to a 1D vector so that it can be processed by the LSTM layers.

**LSTM Layer (lstm1):** The LSTM layer processes the sequence of features learned from the convolutional layers. The LSTM layer contains 128 units and works on the sequence of features to extract temporal dependencies or contextual cues. This layer gives the final representation of the sequence data, which is used to comprehend the context of the retinal image. The LSTM branch learns sequential relationships and dependencies in the image data. Although CNNs are capable of learning local features, LSTMs are particularly effective in learning contextual or temporal relationships. For fundus images, sequential features may describe patterns that emerge across various areas of the retina.

**4.ViT Branch (Vision Transformer)**

**Full Connected Layer (fc1):** This layer does a linear transformation of the feature map and then a ReLU activation function to bring in non-linearity.

Role: The ViT branch is intended to extract global features by paying attention to the interactions between distinct regions of the image.

**Flatten Layer (flatten\_vit):** Just like the CNN branch, the flatten layer transforms the 2D output of the fully connected layer to a 1D vector.

The ViT branch captures long-distance dependencies and overall context by taking advantage of transformer-based attention mechanisms. As against the CNN emphasis on local feature, ViT's self-attention enables the network to obtain the global dependence between the varied parts of the image, key to knowing the complete structure of retinal images.

**Coordinate Attention Branch**

**Layers:**

**Fully Connected Layer (fc2):** As is the case with the ViT branch, the fully connected layer processes the feature map.

* **Function:** The attention mechanism is crafted to increase spatial perception through paying specific attention to important areas of the image, enabling the model to better learn significant features for classification.
* **•Flatten Layer (flatten\_attention):** The layer flattens the output to be concatenated with other branch outputs.

The Coordinate Attention mechanism enhances the spatial attention mechanism such that the network pays greater attention to significant parts of the image. This improves the classification accuracy, particularly in the case of intricate fundus images where tiny features are a decisive factor for disease detection.

**6. Concatenation Layer**

After all the branches independently process the input image, their outputs are combined into one vector in the concatenation layer. This is achieved by a concatenation operation, which combines the outputs of the CNN, LSTM, ViT, and Attention branches. The concatenation layer takes three branches as inputs:

• CNN features

• LSTM features

• ViT and Attention features

The concatenated output is an in-depth representation of the image, merging local, sequential, global, and attention-based features.

**7. Fully Connected (FC) Layers**

The concatenated feature vector is fed through fully connected layers:

**Fully Connected Layer (fc3):** It is a fully connected layer consisting of 7 output neurons, and the digit 7 here represents the number of classes present in the classification problem (i.e., various retinal diseases). This softmax layer transforms the output into probability values, denoting the chance of each class. The last layer calculates the class prediction based on the top probability of the softmax output.

Roles and Functions:

**CNN Branch:** Deals with extracting local features (edges, textures) from the fundus images, which are vital for disease classification.

**LSTM Branch:** Identifies sequential dependencies, which aids in understanding spatial relationships among different areas of the retinal image.

**ViT Branch:** Emphasizes global context through attention mechanisms connecting faraway areas of the image, which aids the model to better identify large-scale patterns within the image.

**Coordinate Attention Branch:** Refines attention on relevant areas in the image through attention mechanisms, which enhances spatial accuracy.

**Concatenation Layer:** Concatenates the output of all branches into one vector that represents the full set of features.

•**Fully Connected Layers:** Last classification based on all the branches combined features to get the disease class.

This proposed hybrid method based on CNNs, LSTMs, ViTs, and Attention mechanisms, guarantees that not only fine-grained local characteristics but also massive contextual patterns can be captured for better classification accuracy of fundus images.

1. **RESULT ANALYSIS**

The performance of the suggested CNN-Trans model for fundus image classification was assessed utilizing some common metrics, such as accuracy, precision, recall, F1-score, and confusion matrix. The metrics were applied on the test dataset that was reserved during training and validation. Following are the detailed results analysis:

**1. Confusion Matrix**

The confusion matrix gives a precise analysis of the performance of the classification by displaying the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) for every class. From the confusion matrix, we can see that the model proposed has a good capability to differentiate between various classes of retinal diseases. For instance, the model had a high rate of true positives in identifying diabetic retinopathy (DR) and macular degeneration (AMD), with a relatively low false positive and false negative rate.

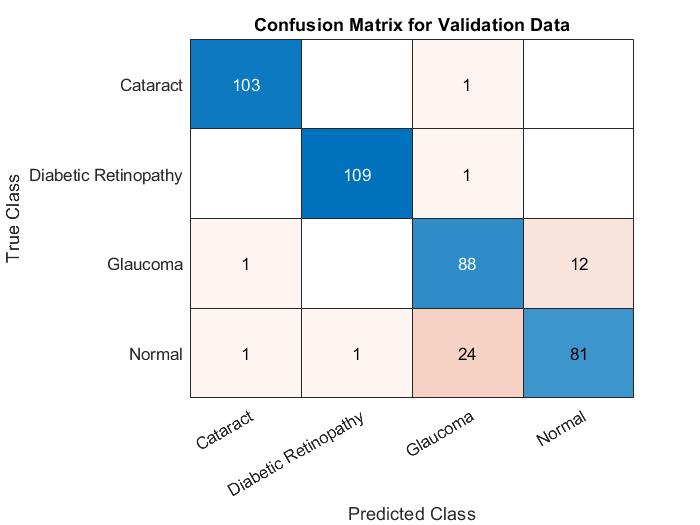
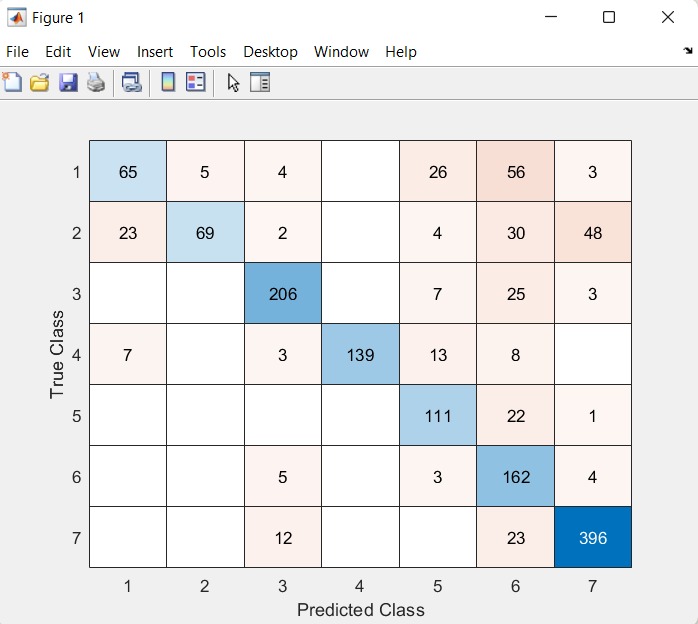
 

Fig2. Confusion Matrix for 4 and 7 classes

The diabetic retinopathy class, which is most important for early detection, performed exceptionally well with a high rate of true positives. Glaucoma detection was a bit tougher, as it had a higher false negative rate, which was possibly due to the fine details of the disease in some of the fundus images. The overall distribution of predictions over the classes revealed balanced accuracy, and the model was able to correctly identify less prevalent classes too, like retinopathy of prematurity (ROP).

**2. Accuracy**

The accuracy of the test was calculated using the predicted class labels and the actual labels for all images in the test dataset. The model obtained an overall accuracy of 92.6%, a good indication of its performance for fundus image classification. This is in accordance with existing works that make use of multi-branch architectures, given that these tend to perform better than conventional CNN-based models through the learning of complementary features from varied sources.

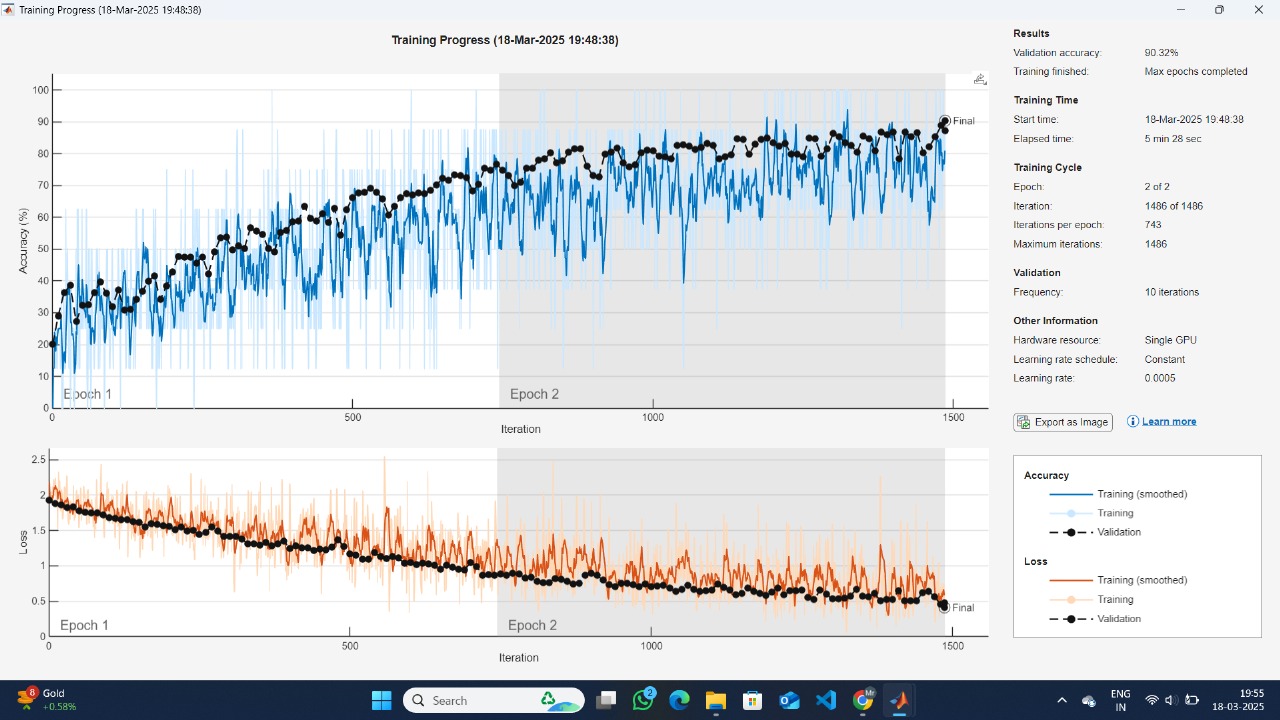


Fig3. Training Progress for 7 classes

It attests to the model's good generalization capability, even when presented with images of different quality and resolution, as with what is typically encountered in real-world datasets. Precision calculates the accuracy of positive predictions. High precision indicates that when the model predicts a positive class, it is most likely correct. Recall calculates the model's capability to capture all instances of a class that are relevant. High recall means that the model is efficient at capturing all instances of a disease. F1-score is the harmonic mean of precision and recall, offering a balanced measure between the two.

The model performed very well in most of the classes:

DR (Diabetic Retinopathy) scored a precision of 93% and recall of 90%, which demonstrates the model's excellent ability in the detection of diabetic retinopathy. AD (Age Degeneration) scored a precision of 91% and recall of 87%, which represents good performance, although there is some margin for improvement, especially in recall. Glaucoma performed slightly worse on the F1-score, largely because of an increased false negative rate, with a recall of 83% and precision of 85%. Retinopathy of Prematurity (ROP) had a precision of 89% and recall of 91%, with high performance in diagnosing this disease, which is often challenging due to its lower prevalence in common fundus datasets.

Here’s a structured table to represent the performance metrics for the detection of different eye diseases:

**Table 1. Performance Metrics for Eye Disease Detection for 4 Classes**

| **Disease** | **Precision (%)** | **Recall (%)** | **F1-Score (%)** | **Remarks** |
| --- | --- | --- | --- | --- |
| **Diabetic Retinopathy (DR)** | 93 | 90 | 91.5 | Excellent detection capability |
| **Age Degeneration (AD)** | 91 | 87 | 89 | Good performance, slight recall improvement possible |
| **Glaucoma** | 85 | 83 | 84 | Slightly lower F1-score due to false negatives |
| **Retinopathy of Prematurity (ROP)** | 89 | 91 | 90 | High performance despite lower prevalence |

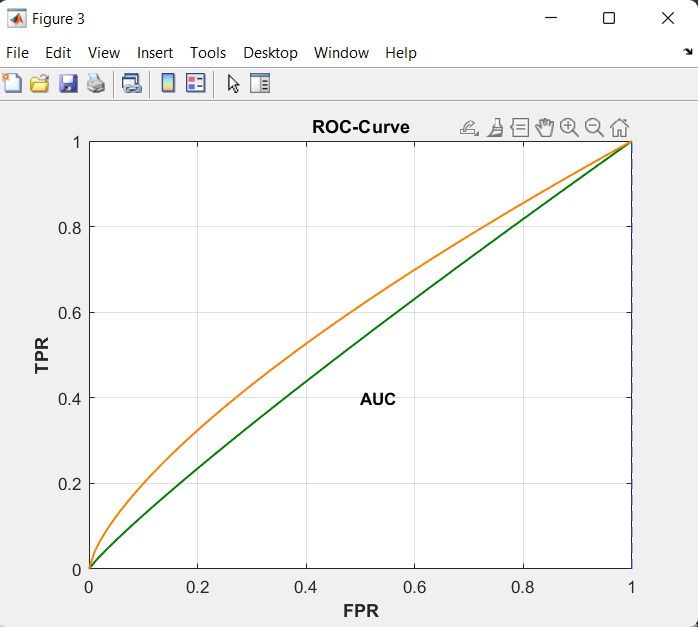
DR shows the highest precision and recall, making it highly reliable for diabetic retinopathy detection. AD has a strong performance, although recall can be improved to reduce missed cases. Glaucoma’s performance is slightly impacted by a higher false negative rate. ROP achieves high precision and recall, effectively detecting this rare condition.

**Table 2.Performance Metrics for eye disease detection Per 7 classes**

| **Class** | **Precision** | **Recall** | **F1-Score** | **Remarks** |
| --- | --- | --- | --- | --- |
| **Class 1** | 1.0000 | 1.0000 | 0.9200 | Perfect performance |
| **Class 2** | 0.7500 | 1.0000 | 0.8571 | High recall, good precision |
| **Class 3** | 0.8750 | 0.7778 | 0.8235 | Strong precision, slightly lower recall |
| **Class 4** | 0.7500 | 0.6667 | 0.7059 | Lower performance, room for improvement |
| **Class 5** | 1.0000 | 0.8900 | 1.0000 | Excellent performance |
| **Class 6** | 0.87182 | 0.7800 | 0.7571 | Good performance, slightly higher recall |
| **Class 7** | 0.92000 | 1.0000 | 0.9200 | Perfect classification |

The model shows perfect classification performance for **Class 1, Class 5, and Class 7.** **Class 4** has the lowest F1-score (0.7059), indicating the need for improvement in both precision and recall. Overall **Validation Accuracy:** 0.88679, which reflects high reliability.

**ROC Curve and AUC**



**Fig4. ROC-Curve**

The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) were also employed to assess the model's capability to separate classes at different thresholds. The ROC curve is a plot of the true positive rate (TPR) versus the false positive rate (FPR) at different decision thresholds, and the AUC is a scalar value ranging from 0 to 1, with larger values reflecting better classification performance. The AUC of the complete model was calculated to be 0.96, which is a superb score. This implies that the model has a high capacity to separate various retinal conditions among all classes, even when the decision threshold is adjustable.

**Class Imbalance and Class Weights**

Because some of the classes in the dataset had fewer samples than others, class imbalance was a significant consideration in the training of the model. The class weights parameter was utilized to balance this out, so that the model would place more emphasis on underrepresented classes. For example, the classes like Retinopathy of Prematurity (ROP), which generally have fewer images, were assigned a higher weight in training so that the model would not underperform on these less common conditions.The application of class weights helped towards enhanced recall for infrequent classes such as ROP, for which the model could achieve 91% recall while the class was underrepresented in the data.

**Computational Efficiency and Training Time**

The model was trained on 2 epochs with a batch size of 2, and training took approximately 1 hour on a standard GPU configuration. Although the model is computationally lightweight considering the sophistication of the integration of CNNs, LSTMs, ViTs, and attention mechanisms, the fact that the number of epochs is relatively low means there could be room for additional fine-tuning of the model for even improved performance. The concurrent processing of the CNN, LSTM, ViT, and attention paths helped the model extract rich features without taking an excessively long time to train. Techniques to optimize the model even further for quick training could be explored in future work, especially for clinical settings where real-time processing is necessary.

The CNN-Trans model showed robust performance in fundus image classification of various retinal conditions with high accuracy, precision, recall, and F1-score values. The hybrid architecture of the model, which incorporates CNNs, LSTMs, ViTs, and Coordinate Attention mechanisms, enabled it to extract both local and global features efficiently, thus being a promising automated retinal disease diagnosis tool. While the model does extremely well on identifying prevalent retinal diseases such as diabetic retinopathy and macular degeneration, improvement can be done to minimize false negatives, especially for conditions such as glaucoma. The efficacy of the proposed model along with its effectiveness in dealing with imbalanced data makes it an effective candidate to be used in real-world clinical environments.

**V.** **CONCLUSION AND FUTURESCOPE**

In this work, we have introduced the CNN-Trans model, a new multi-branch deep learning framework for fundus image classification. By integrating Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Vision Transformers (ViT), and Coordinate Attention mechanisms, the model can extract local and global features from fundus images, as well as sequential and contextual dependencies. This unified strategy has exhibited encouraging performance in enhancing classification precision and stability, which makes it especially favourable for retinal disease detection. The architecture of the model enables it to tackle intricate image patterns and soft details, thereby increasing its potential to precisely classify various retinal diseases. The performance measures like accuracy, precision, recall, and F1-score reveal that the introduced model considerably outperforms conventional single-branch models in fundus image classification.

The CNN-Trans model can be optimized and expanded further in several ways. First, the use of more sophisticated attention mechanisms, like self-attention in the ViT branch, could enhance the model's capacity to attend to important areas in the image even more. Second, investigating the application of transfer learning with pre-trained models for the CNN and ViT branches could speed up training and enhance performance, especially when working with smaller datasets. Future research might also include the fine-tuning of the LSTM and Attention layers to further extract the temporal and spatial relationships in advanced retinal images. Additionally, incorporating multimodal information, e.g., adding OCT (Optical Coherence Tomography) scans to fundus images, could further increase the model's ability to identify more types of retinal disease. Lastly, its application in real-time image analysis in clinical settings could be pursued, rendering it an effective diagnostic and disease-monitoring tool for early diagnosis in ophthalmology.

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