Early Dyslexia Detection and Classification Using Residual Dense-Assisted Multi-Attention Transformer and Eye Tracking Data

*[1]G.R. Priyasri, [2]M. Uma Devi

*[1,2]Department of Computing Technologies,
SRM Institute of Science and Technology, Chennai, India.

[1]*Priyabalaji.tvr3@gmail.com
[2]umadevim@srmist.edu.in

Abstract. Dyslexia is a neurological disorder which leads to learning disabilities mainly in reading. This learning disorder affects 5 to 10 % of peoples across worldwide. Usually, persons affected from dyslexia faces difficulties in spelling, reading and writing fluency. It affects any age peoples and it is not related to their intelligence. It is a hidden reading disability which is crucial to diagnosis. But an early and easy diagnosis of dyslexia will improve the abilities of affected peoples using specialized software or tools. The major objective of this model is to present a clean and accurate screening model for dyslexia classification using eye tracking movement data. This paper proposed a residual dense-assisted multi-attention transformer model for detecting and classifying dyslexia with data normalization. In this paper the risk of reading difficulties can be analyzed by the tracking movement data which is better than any screening methods. The proposed research attained high accuracy, precision, recall, F1-score, sensitivity and specificity of 99.48 %, 99.32 %, 99.27 %, 99.41 %, 99.53 % and 99.26 % respectively. A novel transformer based residual dense network with multi-attention module is developed to detect and classify the dyslexia disorder. This research is done with the eye tracking data with large number of attributes. This work attained high accuracy which implies that the proposed model outperformed well on others.

Keywords: Depression, Automation Systems, Gated Convolutional, Capsule Transformer, Speech-Based.

1. Introduction

The name dyslexia, which denotes trouble with words, comes from the Greek language. This is a common hereditary impairment that develops over time and is present from birth in persons of all ages [1]. Among the different types of disabilities, this is the most prevalent and prevalent learning disability. People who have trouble recognizing sounds and connecting words and letters, as well as those who struggle with reading or writing, are deemed to have dyslexia [2]. Typically, symptoms of dyslexia is apparent from a person reaches a level of literacy and a particular age. Without proper acknowledgment and accommodations, the students with dyslexia are

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more likely to struggle in classrooms [3]. Developmental dyslexia may affects the academic performance of students, and may lead to anti-social behavior and depression. Early diagnosis may improve the future academic performance and enhances the life quality [4].

Traditional methods for detecting dyslexia depends on reading texts and words, writing and working memory. Dyslexia is mainly considered as a visual processing problem and is known as word blindness. All of them knows that memorizing the order of letters in a word is the first step in learning to read [5-6]. Due to ICT [7], which allowed for the digitization of various screening procedures, the most frequent screening tests like CASL, WRMT, GSRT, TWEL, TAPS, and CTOPP-2 are available on the web [8]. In order to improve the accuracy and reliability of dyslexia prognosis, modern technologies have taken neurological movements into account. The majority of doctors and nurses use EEGs to diagnose dyslexia [9].

The brain signals are gathered as electroencephalogram (EEG) [10] signals which represents the spontaneous activities of brain with eyes opened and closed. The EEG signals plays a crucial role in managing the brain activities [11]. Using appropriate datasets, the majority of previous research has favoured Machine Learning (ML) [12] for the detection of dyslexia in children. Eye tracking, EEG, handwriting and test score datasets were utilized to detect the dyslexia [13]. ML methods do not process raw data and to overcome this issue, a subset of ML named Deep Learning (DL) is developed. DL models do not specifically perform feature extraction models, which is intrinsic to conventional models. To stimulate the brain function, DL utilizes Artificial Neural Networks (ANN) but it need some alteration and development to perform such activities hence, they remained the same [14].

Most of the experiments were uses small datasets from clinics which leads to generalizability issues. But, eye movement recordings are gathered from several clinics, laboratories include large amount data, which resolve the generalizability issues [15]. Furthermore, eye movement data has proven the efficiency in reading behavior of dyslexia disorder detection. The examination of eye movement during the reading or writing tasks, improves the intervention for those who faces difficulties while reading or writing [16]. Some of the scenarios like lacking of big datasets and generalizability issues, a transformer based models with advanced techniques were utilized to address these issues [17].

1.1 Motivation & Contribution

Developmental dyslexia and acquired dyslexia are two main categories of the disorder. Both acquired dyslexia (AD) and developmental dyslexia (DD) are identified in early childhood; however, the latter is often the result of brain injuries. The DD can be detected by noticing the eye movements of the persons who are affected by dyslexia. Differences across populations in virtually all prior eye tracking studies with and without dyslexia have suggested that dyslexics' visual impairments are reflected in their eye movements. When used to the identification of dyslexic children, eye tracking in conjunction with advanced learning has the potential to provide screening models that are fast, objective, and accurate. Dyslexia detection is improved with several advancements but there exists some of the limitations like generalizability issues, lack of datasets, detection accuracy rate is low and so on. These limitations motivates to do this research. Hence, an efficient eye tracking data based dyslexia detection is developed for quick and accurate model for dyslexia diagnosis. The major contributions of the proposed work is described as follows:

- To capture both spatial and temporal patterns of eye movements for dyslexic classification an advanced transformer based model is employed.
- To enhance the critical performance of dyslexic diagnosis an attention mechanism is utilized.

The rest of the paper is prepared as, Section 2 comprises of collected works survey based on dyslexia detection approaches and their limitations. The novel proposed methodology is elucidated in Section 3. Section 4 illustrated with the results of the proposed models and performance evaluation and discussion. Section 5 concluded with future work and limitation of this work.

2. Literature Review

A 3D neural network based dyslexia detection using functional magnetic resonance imaging was developed by Zahia et al. [18] to reduce the frustration of the affected children. This method is composed of the brain activities of the affected patients during reading or writing tasks. Initially the pre-processing steps are included to retrieve the brain activations. The collected 3D volume brain activation are classified using 3D convolutional neural network (3D-CNN). In addition to that, a 4-fold cross validation is performed to reduce over fitting and assess the generalizability. The classified framework is appraised using some of the performance metrics like accuracy, sensitivity, precision, specificity and F1-score. The main limitation in this work is limited number of participants.

Early recognition of dyslexia based on ensemble models are recommended by Ahmed Saeed et al. [19]. This work considers some ensemble models on large dataset. The dataset is freely available on kaggle and consists of 196 attributes with 3644 subjects with two dyslexic and non-dyslexic classes. To minimize the errors, an ensemble approach is initiated. This approach is carried out in three phases including ensemble pool framework, cross validation and dimensionality reduction with some of the ensemble learning methods. Adaboost, bagging, subspace and RUSBoost ensemble methods are analyzed for experimental evaluation. The performance of the ensemble approach is validated using the metrics such as F1-score, Area under Curve (AUC), accuracy, recall and precision.

A ML ensemble model based dyslexia detection through visual continuous performance task (VCPT) was established by Zaree et al. [20]. The EEG signals were used to evaluate the experiment. This study involves pre-processing, event related potential (ERP) extraction, feature selection and ensemble learning with five classifiers such as Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbor (KNN), Latent Dirichlet Allocation (LDA) and Naïve Bayesian classification (NB). Feature extraction using Principle component analysis (PCA) highlights the EEG feature differences. Accuracy, Sensitivity, specificity and F1-score are the operating metrics used for the performance of ensemble models and attained 87.5 %, 81.2 %, 93.7 % and 86.92 % respectively.

An efficient ML based dyslexia identification using feature optimization model is demonstrated by Ahmad et al. [21] to utilize the potential of a unified gaming test data. This experiment comprises of feature mapping, feature normalization, model tuning and performance evaluation. An efficient PCA is utilized for mapping the features of the gaming attributes. Artificial Neural Network (ANN) with PCA is the ML framework utilized in this approach and attained an accuracy of 95 %. The PCA reduces computational overhead of the model. DL would be used instead of ML approaches which increases the performance accuracy of the model.

Using a VGG-16 network, Ivan et al. [22] created a system for detecting dyslexia in youngsters based on eye tracking data. The 30 participants in this study are limited to the eye tracking data collected by SMI-RED-m. This experiment consists of pre-processing, visualization and DL based VGG-16 classifier for detecting dyslexia. The performance accuracy is evaluated on the basis of instance and subject levels. The model attained a subject accuracy of 87 % which is complex than instance accuracy of 79 %. The main limitation of this work is it only utilizes a specific sensor type data instead of using other signals by EEG, electro dermal activity (EDA) and heart rates.

A CNN based dyslexia detection using EEG signals are developed by Andrés et al. [23] using a correlation component named Singular Spectrum Analysis (SSA). This SSA is used to split or divide the raw signal into several oscillatory components. The CNN based SSA extracts the relevant features from EEG signals. The classification is carried out by the combination of different convolutional layers including 2D convolutional layers with 16, 32 and 64 filters. Incorporating a ReLU activation function and a softmax layer into a dense fully linked layer. Classification performance is validated using accuracy, specificity and sensitivity.

Dyslexia detection of ML models with eye movement data was developed by Raatikainen et al. [24]. The dataset employed in this study was collected from project eSeek and obtained from 165 youngsters. The ML classifiers like SVM and Random Forest (RF) are utilized for dyslexia detection. SVM maps the input vector into high dimensional data to separate the classes and reduces generalization errors. RF is utilized to join the decision on the class. The performance of the ML models were evaluated using accuracy and recall and attained 89.7 % and 84.8 % respectively.

A convolutional neural network based dyslexia detection using electro-oculogram (EOG) signals are suggested by et al. [25] to provide the appropriate learning opportunity and social environment for those who affects by dyslexia. This approach utilizes 1D CNN is used to detect the dyslexia. This EOG signals are pre-processed using filtering technique and segmented the signal samples. These samples are fed into 1D-CNN and classify the signals as dyslexia and healthy. The classification model comprises of two convolutional layer, batch normalization and max pooling layer of two and two fully connected layer with dropout activation and softmax layer. Accuracy, specificity, F1-score and sensitivity are validated for the performance measure. This 1D-CNN attained overall classification accuracy of 98.70 %.

Detecting school aged children's dyslexia in early stages using long short term memory (LSTM) and eye tracking movement technology was developed by Gomolka et al. [26]. This experiment analyze 145 participants under the age of 9 years of 66 girls and 79 boys. This study makes use of eye tracking tools such as Pupil Core v2.0182 and Pupil invisible. To determine the efficacy of the training set, this study used a Benton test. Long short-term memory (LSTM) examines how people use spatial and temporal methods to recognize scenes. A CNN based relevant feature extraction attained an accuracy of 95.6 %.

Dyslexia identification with Chinese dictation task was demonstrated by Liu et al. [27] using a hybrid method named CNN-positional-LSTM-attention mechanism. This classification model combines the strength of positional encoding with CNN, bidirectional LSTM (Bi-LSTM) and multi head self-attention module. A total of 869 scanned photographs including encoded responses written by hand make up the collection. These dataset images were pre-processed to reduce the computational cost. After that, feature extraction, positional encoding, sequence modeling, attention mechanism and classification is carried out to detect the dyslexia. Accuracy, Sensitivity, Specificity and AUC are evaluated on the prediction model.

An Artificial intelligence (AI) based dyslexia detection with some ML approaches are developed by Rajan et al. [28] to reduce the computational cost and time. The dataset named speech signals were used in this study was gathered from publicly available kaggle repository. The computational model is implemented in Raspberry Pi. The classification is carried out by optimized SVM model which classifies the features into dyslexia and non-dyslexia. The performance of this model is estimated using metrics. In addition with that, reinforcement learning is employed to provide personalized interactive assistance for dyslexic patients.

A ML based dyslexia detection and segmentation of the brain region are developed by Sangeetha et al. [29] to identify and classify the several dyslexia images. This dyslexia detection and classification process involves pre-processing, feature extraction, segmentation and classification. The ML classifier XGBoost is utilized for classifying the attained features. The performance of this model is estimated using some metrics. The XGBoost classifier categorize the extracted features into normal and abnormal on the basis of tumor region presented in the brain.

Early identification of dyslexia detection using ML based architecture was presented by Senthilselvi et al. [30] to prevent long term psychological impacts. The dyslexia detection is diagnosed by identifying the eye movement of the persons who is affected by dyslexic disorder. This study employed with input data reading text, model training, classification model selection, model validation, score calculation and disorder prediction. The classification model random forest with grid search is selected based on comparative analysis with some ML models like SVM, DT, RF and SVM with grid search. Precision, F1-score and recall measures are evaluated for model's performance.

The neurological disorder named dyslexia diagnosis is employed with ML algorithms are demonstrated by Sharma et al. [31]. The detection of dyslexia have been takes place with an online gamified exam. The gamified exercises uses empirical analysis of dyslexic errors and test exercise process for dyslexia related difficulties. This study uses SEER dataset and fed into pre-processing approaches, feature selection and classification. The ML models like logistic regression (LR), RF, DT, KNN and Naïve Bayes are utilized for the classification of dyslexia diagnosis. The performance of this model is validated based on accuracy and Receiver Operating Characteristic (ROC) curve. LR attained high model accuracy of 90 % which outperformed the other four ML models.

Eye movement features based dyslexia detection using machine learning models was established by El Hmimdi et al. [32]. The dataset consists of 187 children's eye movements, 97 children's are with dyslexic and remaining 88 are non-dyslexic. This experiment consists of pre-processing, feature generation using statistical measures, feature selection and classification using ML algorithms. The classification is carried out by aggregation of kernel SVM with Particle Swarm Optimization (PSO) and this model is evaluated with performance metrics comprising accuracy, recall, precision, F1-score and specificity. This model attained better accuracy and F1-score of 96.6 %. **Overview of recent studies related to dyslexia detection is illustrated in table 1.**

Table 1. Previous Study Analysis

Author & References	Approach used	Limitation	Performance metrics
Saeed et al. [19]	Ensemble approach	Detection accuracy is low	F1-score, AUC, accuracy, recall, precision.
Ivan et al. [22]	VGG-16	Data from a specific sensor is used, other types of data are not utilized.	Subject accuracy, instance accuracy
Raatikainen et al. [24]	SVM, RF	DL architectures were not utilized well.	Accuracy, recall
Gomolka et al. [26]	LSTM	Integration of CNN and LSTM were not utilized to increase the detection accuracy	Accuracy

By analyzing various previous studies related to dyslexia detection and classification based on eye tracking data, there exist some of the limitations including, low performance accuracy [19], usage ML methods [22], hybridization methods [26] and so on. These limitations are resolved in the proposed approach. In other words, proposed approach is developed to overcome these shortcomings.

3. Proposed Methodology

Reading fluency is delayed in children with dyslexia because the neurodevelopmental disorder has a negative impact on the accuracy and speed of word recognition. Early detection of those at risk for learning disabilities could be facilitated by rapid and automated screening methods based on important objective reading assessments. The proposed method was created with the aim of recognizing and classifying dyslexia. **The general workflow of the proposed model is described in figure 1.**

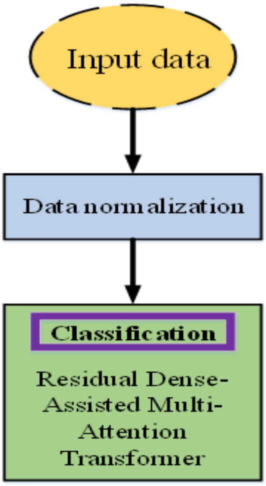


Fig. 1. Workflow of proposed approach

In this study introduced an advanced technique for dyslexia classification using eye tracking data. The process begins with data normalization for transforming data into a standard format, typically between 0 and 1 or -1 and 1. After that normalized data is subject to advanced transformer model named as Residual Dense-Assisted Multi-Attention transformer for early dyslexia detection and classification using eye tracking data. It can be employed to capture both temporal and spatial patterns in the eye movements. Attention mechanisms can enhance the focus on critical dyslexia indicators. The model is trained and validated using cross validation techniques to evaluate performance.

3.1 Residual Dense-Assisted Multi-Attention Transformer

The input data is to be normalized for transforming data into standard format. This normalization measures the input feature values and set from 0-1 series. To set this, take each value and subtract the minimum value. Then, divide the results by the range of features. The data is then standardized and used to classify dyslexia based on eye movement using a proposed innovative transformer model called Residual dense-assisted multi-attention transformer. **The architecture of proposed model is depicted as figure 2.**

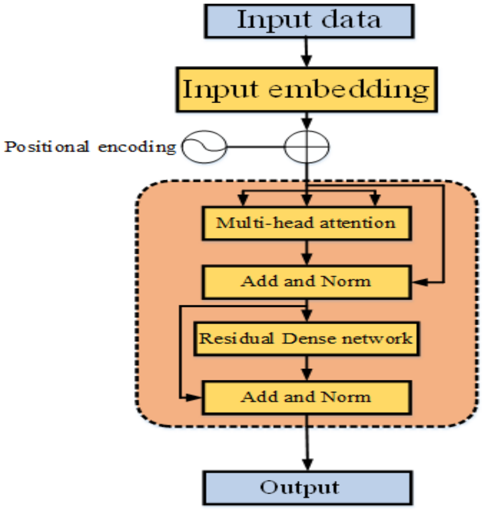


Fig 2. Architecture of proposed model

The proposed transformer model integrates the strength of multi-head attention [33] transformer network and residual dense network. The multi-head self-attention (MHSA) layer of the transformer can anticipate future time steps and seek for different ones at the same time. In order to decrease the number of trainable network parameters, the mel-frequency cepstral coefficients (MFCC) input features are mapped into the transformer block. The input length determines the size of the key-value pairs (K,V), which are utilized by the transformer blocks. The encoder's secret state contains keys and values. (Q,K,V) was used to map the decoder's output from K-V pairings. After adding up all the key-values of the input representations, the decoder produces the output. Every concealed state, key, and sequence length-scaled dot product is the self-attention of the transformer. The self-attention module is represented as,

$$Attention\,(Q,K,V)=soft\max\left(\frac{QK^{t}}{\sqrt{n}}\right) \tag{1}$$

To assessment an over-term with dissimilar weight of the input sequence, a multi-head self-attention can be utilized. A weight matrix obtained from integrating the output of each attention head can reduce the dimensions of encoder state. The mathematical expression for estimating a softmax prediction is illustrated as follows,

$$Multihead\quad(Q,K,V)=[H_1;H_2;\ldots,H_n]w_o \tag{2}$$

$$H_p=Attention\left(Q\,w_p^{Q},Kw_p^{K},Vw_p^{V}\right) \tag{3}$$

Where, the learnable parameter metrics are represented as Qw_p^Q , Kw_p^K and Vw_p^V and the multi-head weighted layers are denoted as w_o . The transformer encoders four identical stacked blocks are used to categorize the features or characteristics. There is an MHSA and a fully connected feed forward layer in every stackable block. After MHSA, normalization and skip connections are added. By using the output of MHSA layer, the skip connections maximizes the original embedding. Normalization and batch normalization is similar to each other. During the process of testing, the norm layer is additionally added, while the batch normalization is used to adjust the sequential inputs. The combined embedding receives the normalizing layer after the residual connection. A one-dimensional convolution is used by the residual dense network (RDN) to classify the features as either positive or negative. Figure 3 below shows the RDN architecture.

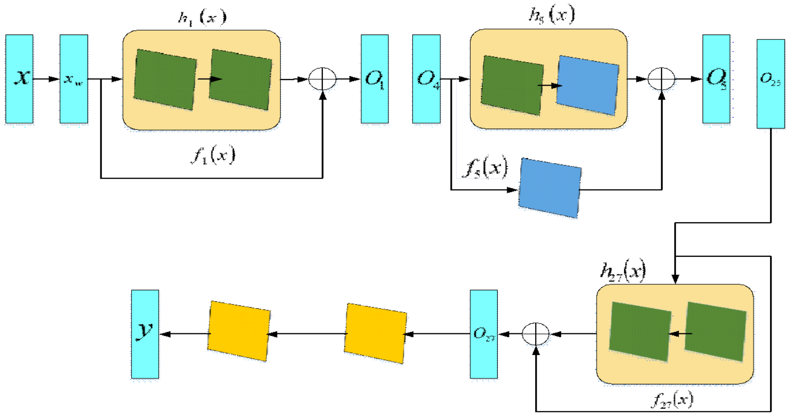


Fig 3. Structure of Residual Dense Network

The RDN consists of two convolutional layers with 27 blocks. Some of the blocks including 5, 8, 11, 14 and 17 have two-stride residual connections which indicates a half dimensionality reduction and the remaining were used by residual connection. The outcome of the residual block was expressed as,

$$O=h(x)+f(x) \tag{4}$$

Where, the convolutional layers block is signified as $h(x)$ and the first layer's input is expressed as x . The strided convolutional layers forms the residual function which is denoted as $f(x)$. A batch normalization and ReLU activation function replaces each convolutional layer. In addition, the output was reduced to a binary result by the last two independent convolutional layers.

4. Results and Discussion

This section involves dataset description, system configuration and performance evaluation and discussion part of the proposed approach. This section clearly enlightens why the suggested model is efficient than any other existing models.

4.1 Dataset description

The dyslexic dataset is provided in the form text file with the extension of .txt. The dataset used for this experiment is gathered from internet resources and consists of 185 subjects. From the experiment on Kronoberg reading development project, 2165 individuals from age 8 to 9 are analyzed, among them 103 subjects including 82 males and 21 females are miscarried to advance reading aids at normal rate.

https://figshare.com/collections/Screening_for_Dyslexia_Using_Eye_Tracking_During_Reading/3521379/1[34]

4.2 Experimental setup

In dyslexia detection the dataset described in section 4.1 were utilized to evaluate the proposed model, because this dataset meets all the criteria. A 5-fold cross validation is employed to guarantee the model's stability and generalizability. The samples are divided 8:2 between testing and training. **System configuration used in this research is illustrated as table 2.**

Table 2. System Configuration

Components	Particulars
Platform	Tensor flow 1.13.1
RAM	8 GB
GPU	RTX 3090
Activation function	ReLU
Residual dense network	27 blocks

4.3 Performance metrics

The performance of the proposed model is appraised based on some of the metrics like accuracy, F1-score, precision, sensitivity, specificity and recall. **Mathematical representation of these measures are described in table 3.**

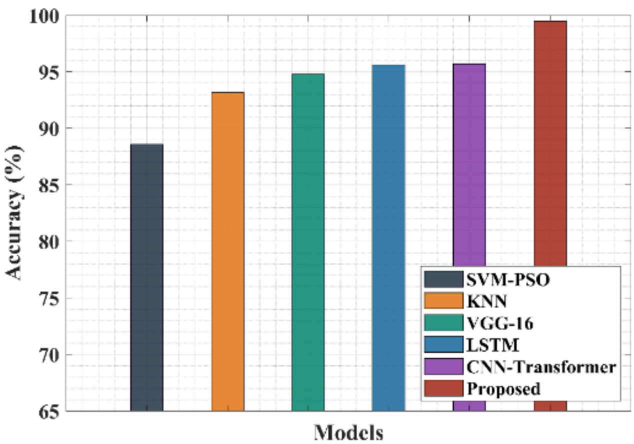
Table 3. Performance Metrics Description

Performance metrics	Expressions
Accuracy	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$

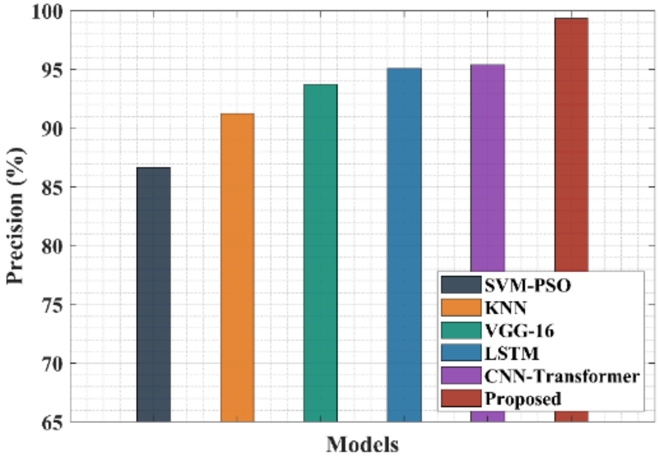
Precision	$\text{Precision} = \dfrac{TP}{TP+FP}$
F1-score	$F1-Score = 2*\dfrac{precision \ * recall}{precision \ + recall}$
Sensitivity	$Sensitivit\ y = \dfrac{TP}{TP+FN}$
Specificity	$Specificit\ y = \dfrac{TN}{TN+FP}$
Recall	$\text{Recall} = \dfrac{TP}{TP+FN}$

4.4 Performance Evaluation

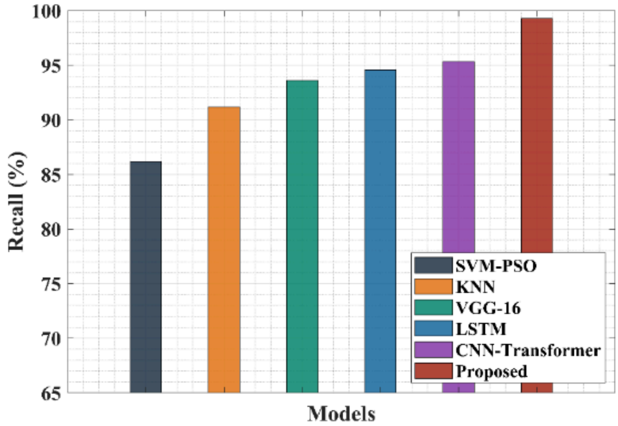
The performance metric measures are validated with some of the existing tactics like SVM-PSO, KNN, VGG-16, LSTM and CNN based transformer model to prove the efficacy and potential of the proposed approach for detecting the dyslexia. **The performance of all the mentioned metrics are depicted in figure 4.**



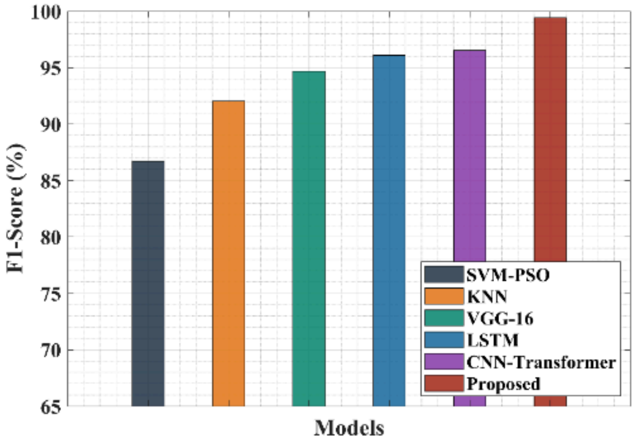
(a) Accuracy assessment of proposed with existing models



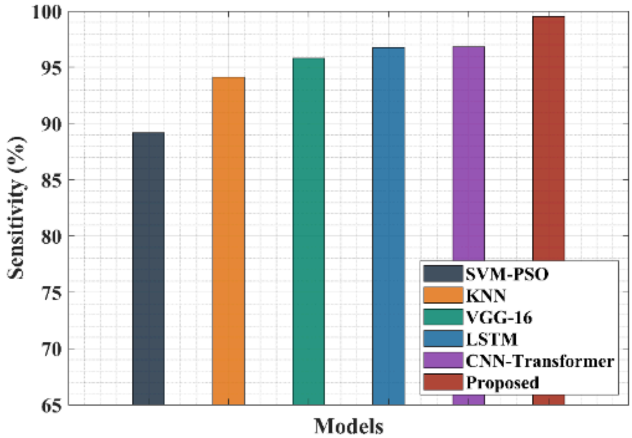
(b) Precision assessment with existing models



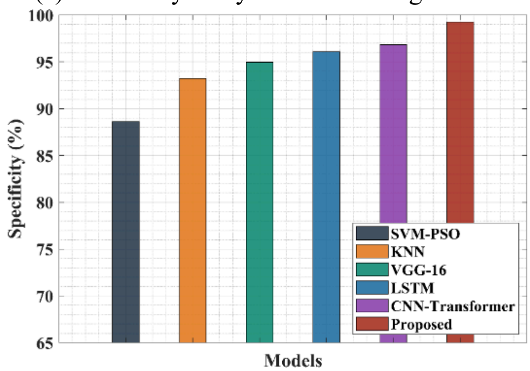
(c) Recall assessment with previous models



(d) F1-score assessment with previous approaches



(e) Sensitivity analysis with existing models



(f) Specificity comparison with previous models

Figure 4 (a-f). Performance metric comparison with existing models

The figure above clearly shows that the suggested residual dense assisted multi-attention transformer model achieved great performance in terms of sensitivity, specificity, accuracy, recall, and F1-score. The accuracy of the suggested method is 99.48 % which indicates higher performance, is due to the normalized data is accurately classified. Better accuracy resolves the generalizability issues. The precision metric of proposed model is 99.32 % which correctly classified the eye movement data based on the features. Recall metric of this approach is 99.27 %, which correctly identifies the false negatives. Increase in precision and recall significantly increases the F1-score value and the suggested model attained 99.41%. As already known that, increase in F1-score, recall and precision the sensitivity and specificity values also increases. The sensitivity and specificity of the proposed approach is 99.53% and 99.26 % respectively. This indicates that the proposed model performed well on other existing models. **The performance metrics analysis is illustrated in table 4.**

Table 4. Performance Metrics Comparison with Existing Models

Performance metrics	SVM-PSO	KNN	VGG-16	LSTM	CNN-transformer	Proposed
Accuracy (%)	88.58	93.16	94.81	95.63	95.70	**99.48**
Precision (%)	86.65	91.24	93.71	95.08	95.39	**99.32**
Recall (%)	86.19	91.16	93.59	94.58	95.35	**99.27**
F1-score (%)	86.70	92.03	94.67	96.09	96.54	**99.41**
Sensitivity (%)	89.17	94.14	95.83	96.75	96.84	**99.53**
Specificity (%)	88.64	93.23	94.96	96.08	96.83	**99.26**

4.5 Discussion

The presented transformer based dyslexia detection outperformed well with eye tracking data, which is proved in performance evaluation section. Several existing methods were analyzed with the proposed model to prove the efficacy of this research. Saeed et al. [19] developed an ensemble model based dyslexia detection using a publicly available dataset. This approach failed to analyze the advanced deep learning models, while uses adaboost, bagging, subspace and RUSBoost for dyslexia detection. This ensemble models provides over fitting issues. But the proposed model uses a RDN based transformer model with multi attention module. Here the 1D convolutional layer is replaced with RDN layer to accurately classify dyslexia. Several previous approaches failed to normalize the data instead it uses feature selection models. A normalized data can give the accurate prediction and classification. In some of the dyslexia detection approaches, uses only limited number of data. Likewise Ivan et al. [22] uses an eye tracking data with limited number of attributes and subjects. This lead to limited classification, this limitation is overcome by the proposed transformer model, which uses a large dataset with 185 attributes to reduce generalizability issues and improve the scalability of the model. With the recent advancements, most of the researchers employed advanced models like deep learning models. But Raatikainen et al. [24] developed a machine learning model based dyslexia detection. SVM and RF are the efficient classifiers for classifying the data. But they have some limitations like stability and low predictive accuracy. Hence the proposed model utilizes a deep learning model residual dense attention module for dyslexia detection. The residual dense network classifies the optimal features into positive and negative binary sequence for detecting dyslexia. Among all these analysis, the potential and efficiency of the proposed model has been proven. Some comparative analysis of proposed with existing model is described in table 5.

Table 5. Comparative Examination with Prevailing Approach

Approaches	Accuracy (%)
Hybrid kernel SVM-PSO [32]	95.11
Spectrum features + CNN [35]	96.6
CNN + Transformer [36]	98.21
Proposed	**99.48**

5. Conclusion

In this research, a novel dyslexia detection and classification in peoples based on a transformer model with eye tracking data. The eye movements of a dyslexic peoples having longer fixations and longer reading times on compared with normal peoples. To identify dyslexia, this study details the process of integrating eye movement data with a Residual Dense Assisted Multi-attention Transformer model based on deep learning. This model is an attempt to use a DL model with eye tracking measurements to predict dyslexia. According to this technique, eye tracking data may be able to identify dyslexia at an early stage. The proposed research attained high accuracy, precision, recall, F1-score, sensitivity and specificity of 99.48 %, 99.32 %, 99.27 %, 99.41 %, 99.53 % and 99.26 % respectively. This proposed model outperformed well on other existing models. Nowadays, eye movement tracking measures are more affordable and are associated with more measures like mouse tracking. Eye tracking has wide range of applications in medical field, neuroscience, gaming and psychology. The main limitation of this work is, it only uses eye movement data of the peoples for identifying the dyslexia. Dyslexia detection can be identified and classified by some other measures including brain signals. Other areas of study involving eye tracking, such as neurology, gaming, and psychology, can benefit from this work as well.

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