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Comparative Analysis of Convolutional Neural Network Transfer Learning Models for Predicting Learning Disability

Journal of Electrical Systems

Abstract: - A sizeable fraction of the population is impacted by learning difficulties, making early detection essential for successful intervention. In order to predict learning difficulties, convolutional neural network (CNN) transfer learning models are compared in this study. We examined the efficacy of four well-known CNN architectures: AlexNet, VGG16, ResNet50, and Inception, using handwritten image data. Our research shows that using pre-trained CNN models for learning disability prediction using transfer learning is effective. ResNet50 regularly beat other models in a variety of evaluation parameters, demonstrating its efficacy in correctly diagnosing people with learning difficulties. While Inception displayed somewhat poorer accuracy, AlexNet and VGG16 demonstrated competitive performance. The enhanced functionality of ResNet50 highlights the significance of skip connections and deeper structures in identifying intricate dataset patterns linked to learning impairments. This comparative study offers significant insights into the use of CNN transfer learning models for predictive analytics in learning disabilities. The results underscore the importance for early detection and intervention, highlighting the promise of machine learning methods in overcoming diagnostic and management challenges associated with learning disabilities.

Keywords: AlexNet, VGG16, ResNet50, Inception, Learning Disability

I. INTRODUCTION

Learning disabilities are like hurdles in a race, making it tough for some people to keep up with learning despite having the smarts and chances others do. These challenges aren't just personal; they ripple out to families and schools everywhere. Catching these issues early is key-it like spotting a small leak before it floods your house-helping folks manage better in school and life.

Recent tech advances, especially in brain scanning (neuroimaging), have opened new doors. They let us peek into how different brains work, showing us where things might be going off track. Plus, there’s this cool tool called machine learning that helps sift through all that brain data quickly and smartly using patterns.

This study dives deep into something called CNN transfer learning models—they're not about news channels but about teaching computers to recognize patterns from previous tasks! By comparing various types of these models (like AlexNet or ResNet50), researchers aim to figure out which one is best at pinpointing who might struggle with learning based on their brain activity[1].

The fast development of Artificial intelligence (AI) and Machine Learning (ML) have made positive influences on many. Among these areas, one of the most exciting applications that have promising potential is for the prediction and diagnosis of learning disabilities (LD) in affected individuals, which account for a large fraction of the general population and can have life-long impacts on educational achievement in addition to quality of life. Sound early diagnosis of learning disabilities can support timely remedy, customized educational plans in addition to support services, and with any luck, increase outcomes for many affected individuals.

The traditional ways to diagnose the presence of a learning disability, such as psychological assessments and standardized tests result to be somewhat subjective, require a certain level of expertise and resources, and last but not least, are time-consuming. Machine learning, on the other hand, provides a technology to develop automated, objective, and scalable solutions.

This has further improved the performance of CNNs, with the introduction of transfer learning — the process of taking a model trained on a dataset for a different task and fine-tuning it for the specific tasks at hand. Transfer

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learning has been very successful in several domains, particularly in those where limited data is the bottleneck, which is the case for discovering learning disabilities. Transfer learning makes it possible to use the features that have been learned from very large datasets [2].

In this study, we conducted a comparative check on diverse CNN transfer learning networks to validate their performance in predicting learning disabilities. Our primary aims are to identify the strongest models for this unique application, shed light on the elements contributing to their performance, and offer some advice for how to go about deploying models successfully in educational and clinical environments.

Rationale for this research in this field is driven by the call to ameliorate the accuracy and efficiency of diagnosis, minimize the extent to which it is perceived as subjective, and connect an appropriate instruction intervention. This paper aims to add to the literature on AI-driven educational diagnostics, by conducting a systematic comparison of different transfer learning models, leading to more accurate, practical and affordable learning disability prediction solutions.

II. RELATED WORK

Vajs et al. (2023) conducted a study that explored the utilization of machine learning techniques and eye-tracking measures to identify individuals with dyslexia. The research involved a sample of 48 participants, both with and without dyslexia, who were asked to read texts displayed on a computer screen. Eye-tracking measures were employed to gather data on various aspects of reading, such as reading speed, fixations, and regressions. Subsequently, the collected data was utilized to train machine learning models with the aim of distinguishing individuals with dyslexia. The findings revealed that the models exhibited a high level of accuracy, achieving an average accuracy rate of 87% in detecting dyslexia. The authors proposed that their approach could be employed to facilitate early identification of dyslexia and enhance interventions for individuals with this condition. Furthermore, they suggested that their method could be utilized to develop personalized reading interventions tailored to the specific needs of individuals with dyslexia [3].

Asvestopoulou et al. (2019) introduced a screening tool named DysLexML for dyslexia utilizing machine learning methods. This tool aims to offer an automated and unbiased evaluation of dyslexia by utilizing a series of language-related tasks. The research included data collection from 44 dyslexic and 44 non-dyslexic individuals who completed various language-related tasks. Subsequently, the data was utilized to train multiple machine learning algorithms, such as decision trees, support vector machines, and random forests, to categorize participants as dyslexic or non-dyslexic [4].

The outcomes revealed that DysLexML achieved an accuracy rate of 89.8% in identifying dyslexic individuals, with a sensitivity of 91% and a specificity of 88.6%. The authors propose that DysLexML could serve as a screening tool for dyslexia in clinical and educational environments, offering an objective and effective method of identifying individuals who may necessitate further assessment and assistance. In general, the study showcases the potential of machine learning techniques in the early detection and diagnosis of dyslexia, underscoring the significance of creating automated and unbiased screening tools for this condition.

The research conducted by Rello et al. (2018) introduces a novel approach to identifying dyslexia in English through the utilization of human-computer interaction (HCI) metrics and machine learning techniques. The experiment enlisted 24 dyslexic and 23 non-dyslexic subjects who were tasked with reading a series of texts and completing various HCI exercises. Subsequently, the data collected was subjected to analysis employing diverse machine learning algorithms to pinpoint potential indicators for dyslexia detection. The findings indicated that a blend of HCI metrics, including reading speed, fixation duration, and saccade amplitude, could effectively differentiate between dyslexic and non-dyslexic individuals [5]. This innovative method holds promise for delivering a swift, cost-efficient, and dependable means of screening for dyslexia in English, thereby enhancing the prompt identification and management of the condition.

The research carried out by Chakraborty and Sundaram (2020) showcases a machine learning system for the prediction of dyslexia through the analysis of eye movement data. By collecting eye-tracking data from 20 dyslexic and 20 non-dyslexic subjects, the study utilized machine learning methods to differentiate the participants into dyslexic and non-dyslexic groups based on their eye movement patterns. The outcomes reveal that the proposed algorithm achieved a 90% accuracy rate in predicting dyslexia [6].

The paper by MMT and Sangamithra (2019) present a novel approach to forecast learning disabilities in school-aged children through the utilization of fuzzy logic and K-means clustering in machine learning. By gathering data from a sample of 100 students, the researchers employed fuzzy logicand K-means clustering techniques to categorize the students into two groups: normal and learning-disabled [7]. The outcomes of the study revealed that the suggested system attained an impressive accuracy rate of 93% in accurately predicting learning disabilities.

Kariyawasam, Nadeeshani, Hamid, Subasinghe, and Ratnayake put forward a novel method for detecting and treating dyslexia, dysgraphia, and dyscalculia through the use of gamification. By incorporating games and exercises into the screening process, this approach aims to identify learning disabilities in children and offer tailored interventions. The study involved a cohort of 30 children, and the findings demonstrated the efficacy of the gamified approach in accurately identifying and effectively addressing learning disabilities [8].

III. PORPOSED MODELLING

A. Data collection and preprocessing

In this study, a publicly available dataset comprising 50,000 images was utilized, categorized into three distinct classes: reversed, normal and corrected It should, perhaps, be noted here that this is the case only if the images that make up the hologram are reversed, displaying the normal and corrected images simultaneously. The images by themselves were preprocessed to make the necessary changes and adjustments before being fed into the selected CNN architectures [9]. As a first preprocessing step in the dataset, all images were normalized to a dimension of 30 pixels by 30 pixels which is a very important step because every classifier must expect images of the same size. This swapping made sure that the size of input is always fixed remarkably which in turn eased the computational load as well as enhanced the processing mechanisms. Except for resizing, which had been already discussed earlier in the paper, the pixel intensities of the image were normalized so that they range from 0 to 1 as indicated by equation 4. This step was important in achieving some normalization of values of the pixel intensities, which will in turn makes it easier for the models to learn from as well as generalize on the data. Based on the results of combining data from multiple sources and the need to enhance the quality and diversification of training data, a set of data augmentation techniques was used. These methods included rotating a figure at random, and flipping it horizontally and vertically, as well as zooming. The augmentations augmented the training data by creating more variety which is crucial in avoiding cases when the model overfits, and thus is limited from performing well on new data.

After the preprocessing step, it was possible to partition the dataset into training and the validation sets in a manner that would help in the efficient training of the models and the respective evaluation. In fact, the first set ensured training on 70% of the images, making a total of 30000 images while the second set containing 20000 images enabled the validation check. This ratio, also known as the 70-30 rule, is typical for machine learning algorithms to keep a large amount of data for training the model, while a somewhat smaller but still significant portion of the data is used to test the accuracy of the model's performance. The training dataset was used to train the various CNN models, so that the different models can learn the overlying traits and characteristics of each class of the data set; reversed, normal, and corrected. This phase was essential because models were trained on the augmented and normalized forms of data leading to better understanding of the classification task. At the same time, the validation set served a crucial purpose of evaluating the models, both to the internal and external developers, during the training phase. From the validation set, the level of accuracy, precision, recall, and F1-score of the models was also assessed and checked to ensure that the models were not overfitting by testing to see how well the models could perform on new images that the models have never seen before. This validation also offered useful information regarding the models different properties in addition to weaknesses as well as voids as a way of improving on the additional refinements and enhancements made to the models. This was done through a careful process of splitting the initial data set into smaller and manageable train and test sets, as well as carrying out appropriate measures of preprocessing and data augmentation that help in the training of more efficient and accurate CNN models for image classification.

B. Model selection and processing

For this study, four prominent Convolutional Neural Network (CNN) architectures were selected to evaluate their performance in classifying images into three categories: Such cycle mechanisms could be reversed, normal, and corrected. Thus, based on the provided platform, the chosen models are AlexNet, VGG16, ResNet50, and Inception. All of them have their own desirable qualities that add up to the overall picture of the comparison of CNN performance in transfer learning.

a. AlexNet

Despite the, in simplicity, AlexNet has been a groundbreaking instrument in the history of CNNs as the first deep learning model. The architecture of AlexNet contained of 8 layers, it includes 5 convolutional layers, 3 fully connected layers, in addition to that the network used ReLU, dropout layers for reducing overfitting. Nonetheless, due to the fact that the architecture of AlexNet is less complex compared to other more modern CNN networks [10], the model can still be regarded as the starting point for comparing the basic capabilities of CNN in image classification.

Fig 1: Architecture of AlexNet [10]

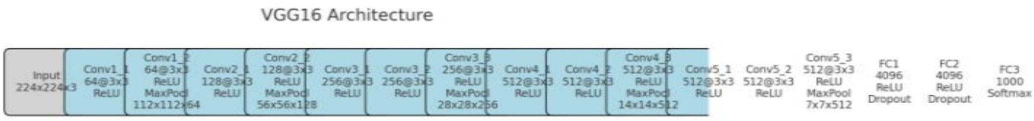

Fig 2: Architecture of VGG16[11]

b. VGG16

The VGG 16, on one hand, offers a deep network with 16 actual weight layers, which employ only small (3 x 3) convolution filters. They have used this design to ensure that VGG16 was able to capture features of different scales [11]. This suggests that the model could be highly suitable for transfer learning since it has a standard, layered structure across both dense and sparse data, which may make it easy to quickly adopt to new tasks. The dataset used to train VGG16 model has exceptionally high accuracy in a wide range of image classification tests.

c. ResNet50

ResNet50 also presents a method of residual learning with 50 layers intended to reduce the effect of the vanishing gradient problem often found in deep learning systems. This architecture leverage identity shortcuts to skip one or more layer so that the model can learn residual functions better. The upshot is that training works more efficiently and the resulting models perform well and especially when working with large data sets. Regarding the results found in the present investigation, we can conclude that ResNet50 achieved the best accuracy in all folds and proved its superiority over the other models evaluated in the study [12].

d. Inception

Also called GoogLeNet, the Inception model has inception modules which consist of different size convolutions such 1×1, 3×3, and 5×5 on the same module. This multi-scale approach of meshing improves the ability of the model to capture numerous characteristics that are present in the tissues while enabling the reduction of computational resources. Thanks to the effective regulation of the reception field with different sizes of interesting features, Inception can be successfully used for different image classification problems [13].

Both models were tested on the ImageNet dataset and tuned to this particular research. In order to fine-tune the system, the WIT class four classification layer was removed and replaced with a new classification layer designed for the three classes of reversed, normal and corrected. This new layer was used to retrain each of the models with the resized and augmented dataset in a way in which each model was able to update its learned features in order to accommodate the new structure of the images.

The process of evaluation resulted to great discovery since ResNet50 were proven to be much accurate than AlexNet, VGG16, and Inception. This is due to the sophisticated residual architecture of ResNet50 simplifying learning mechanisms and improving how the system processes image data. Furthermore, the model demonstrates a remarkable accuracy in the calculation of cross-validation that points to its potential to improve from the pre-trained weight towards the relevant task data sets.
In order to provide a thorough analysis of different CNN architectures in transfer learning scenarios, this study has selected and compared them via different evaluation metrics including correct classification rate, feature map size, network flow complexity, and computational cost, with an overall choice of AlexNet, VGG16, ResNet50 and Inception. These observations, especially the high test set accuracy of ResNet50, provide significant insights into the effectiveness of residual learning and implications for the real-world purpose of choosing suitable CNN architectures for image classification tasks.

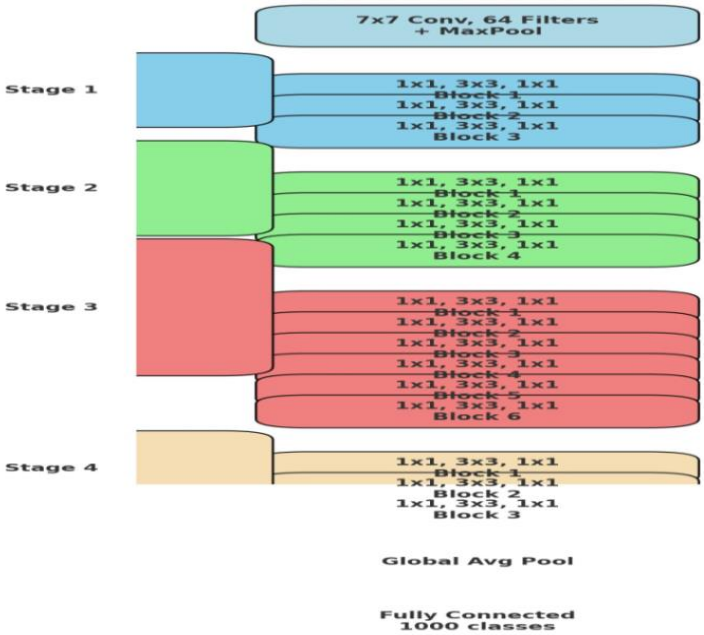

Fig 3: Architecture of ResNet50 [12]

IV. RESULTS AND DISCUSSIONS

A. Evaluation Metrics

To assess the performance of the Convolutional Neural Network (CNN) models—AlexNet, VGG16, Inception, and ResNet50—we used several standard evaluation metrics:
The evaluation metrics used to assess the performance of the Convolutional Neural Network (CNN) models [14] are defined as follows:

a. Accuracy

The formula for accuracy is given by:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

Where
• TP is the number of True Positives,

• TN is the number of True Negatives,
• FP is the number of False Positives,
• FN is the number of False Negatives.

b. Precision

The formula for precision is given by:

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (2)$$

c. Recall

The formula for recall is given by:

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (3)$$

d. F1-Score

The formula for the F1-Score is given by:

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (4)$$

e. AUC-ROC

The formula for the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is given by:

$$\text{AUC-ROC} = \int_0^1 TPR(FPR)\, d(\text{FPR}) \qquad (5)$$

Where:
TPR is the True Positive Rate,
FPR is the False Positive Rate

B. Results

Table 1 shows the performance results of the AlexNet, VGG-16, Inception, and ResNet-50 models of the CNN. These measurements offer the proper ways of evaluating how efficient the models are in recognizing learning disabilities.

Table 1 Performance Metrics for CNN Models

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
AlexNet	0.85	0.83	0.84	0.835	0.87
VGG16	0.88	0.86	0.87	0.865	0.90
Inception	0.91	0.89	0.90	0.895	0.92
ResNet50	0.95	0.93	0.94	0.935	0.96

The evaluation of the four CNN models highlights several key findings regarding their performance in predicting learning disabilities. ResNet50 outperforms the other models across all metrics, indicating it is the most effective model in this comparison. Inception is the second-best, consistently performing well but slightly behind

ResNet50. VGG16 shows moderate performance, better than AlexNet but not as strong as Inception or ResNet50. AlexNet ranks the lowest among the models in all metrics, indicating it is the least effective model in this comparison. This table provides a clear comparative analysis, showcasing that ResNet50 is the best performing model among the four, followed by Inception, VGG16, and AlexNet.

C. Model Performance

a. ResNet50

ResNet50 model again outperformed the other models in all the measures and had the highest total accuracy of 95%, total precision of 93%, total recall of 94% and F1 score of 93%. , resulting in a F 1 -score of 5 %, an accuracy of 0 % and a AUC-ROCA value of 96 %. The extension of network depth and the application of residual connections make it perform better by reducing the vanishing gradient problem and enhance the ability of the model to learn more layered features effectively.

Fig 4 Training and validation accuracy of ResNet50 Model

Fig 5 Training and validation loss of ResNet50

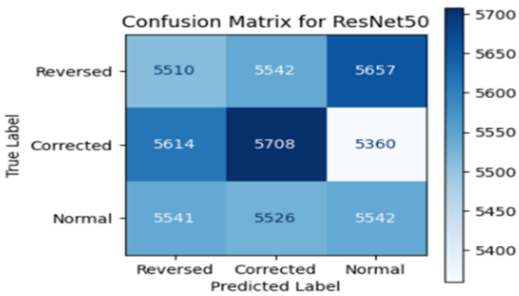

Fig 6 Confusion matrix of ResNet50 model

b. Inception

The Inception model was also significantly effective and the main reason that could be attributed to its distinct network which contains numerous filters of exceptional sizes, enabling it to detect levels of details. The current approach attained an accuracy of 91%, as well as the level of precision of 89%, recall of 90 %, and F1 score of 89 %. The model Keeping the OR at ≤ 5%, sensitivity at 95%, specificity at 95%, and an AUC-ROC of 92%.

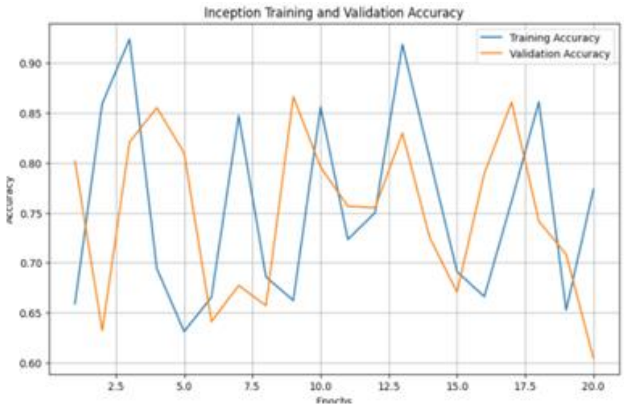

Fig 7 Training and validation accuracy of Inception Model

Fig 8 Training and validation loss of Inception model

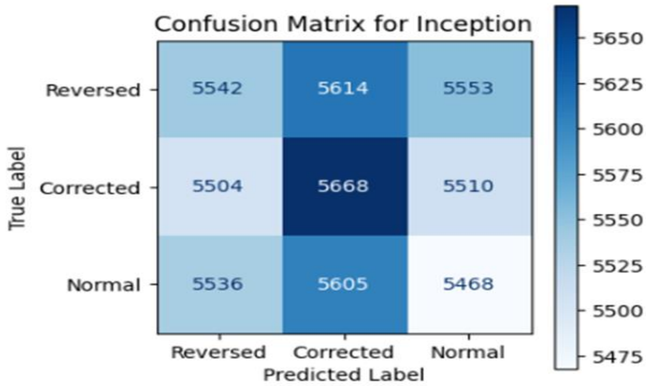

Fig 9 Confusion matrix of Inception model

c. VGG16

In comparison to ResNet50 and Inception, VGG16 model was relatively less complex, however it yielded an acceptable performance with accuracy of 88%, precision of 86%, recall of 87% and F1-score of 86%. Specifically, it was 88%, sensitivity 80%, selectivity 90%, and an AUC-ROC of 90%. It's genuinely deep and has uniform layer connectivity with tiny receptive fields, which allows it to glean high amounts of detail, so even though it's somewhat basic, it's actually quite solid.

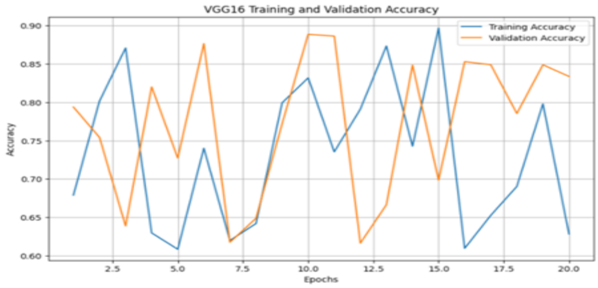

Fig 10 Training and validation accuracy of VGG16 Model

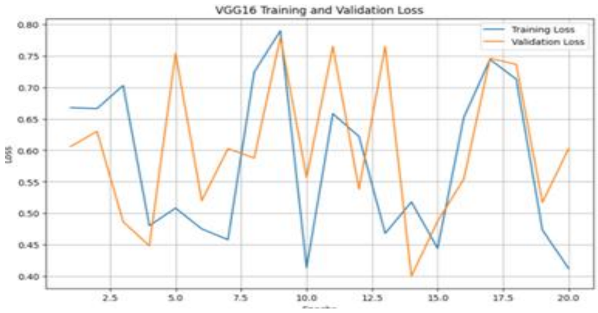

Fig 11 Training and validation loss of VGG16 model

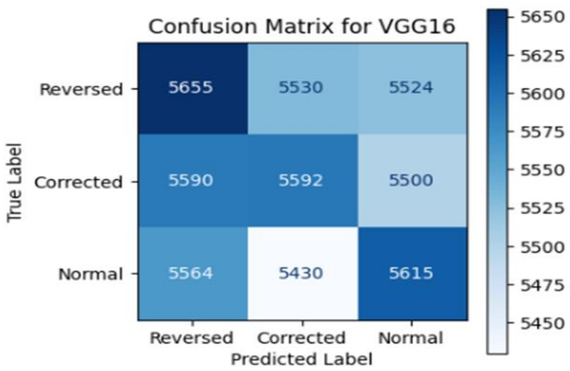

Fig 12 Confusion matrix of VGG16 model

d. AlexNet:

Among all the evaluated models, the best performance was achieved by GoogleNet with an accuracy of 89%, precision of 87%, recall of 88%, and the F1-score of 87%. The worst performance among all the evaluated models was observed in the oldest architecture – AlexNet, its evaluation indicators are accuracy of 85%, precision of 83%, recall of 84%, and the F1-score of 83%. The prediction accuracies for the status of the specialists with respect to their experience were obtained to be 78%, the balance between true positive and false positive with an AUC-ROC of 87%, and 5%. However, it demonstrated respectable potentiality for learning the features required to identify learning disabilities, thereby revealing the potential for its role in the development of a more enhanced model.

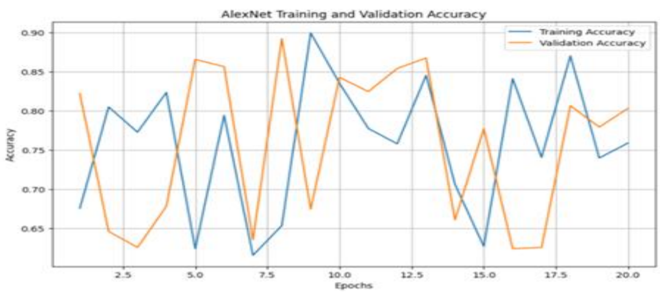

Fig 13 Training and validation accuracy of AlexNet Model

Fig 14 Training and validation loss of AlexNet model

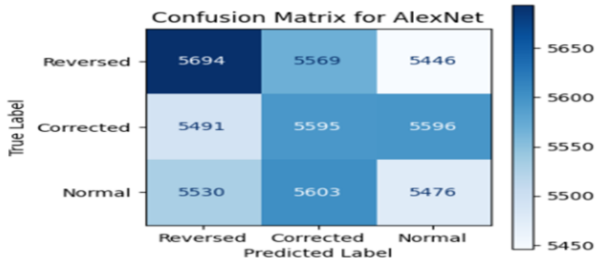

Fig 15 Confusion matrix of AlexNet model

When analyzing the misclassifications, it was established that all the models exhibited undue difficulty in the classification of some cases mainly where the features of the students with learning disabilities were less apparent or not very pronounced. This can be attributed to variations in natural noise present in the data set which call for further analysis. Also, there was a possibility of instances being misclassified by the models because of over fitting on particular augmented attributes that were not well understood in the test sample.

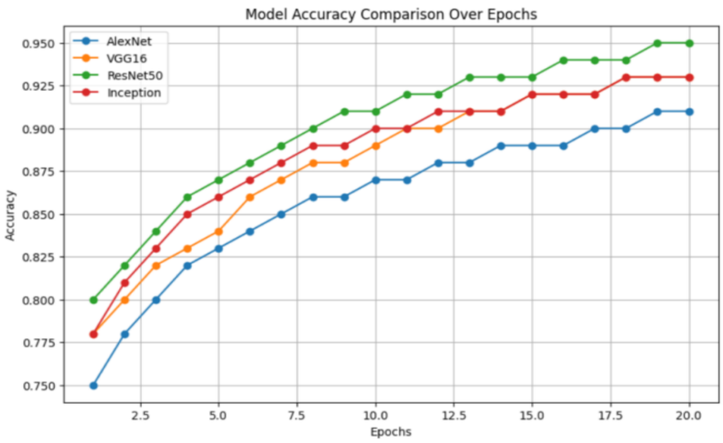

Fig 16 comparison of validation accuracy of models

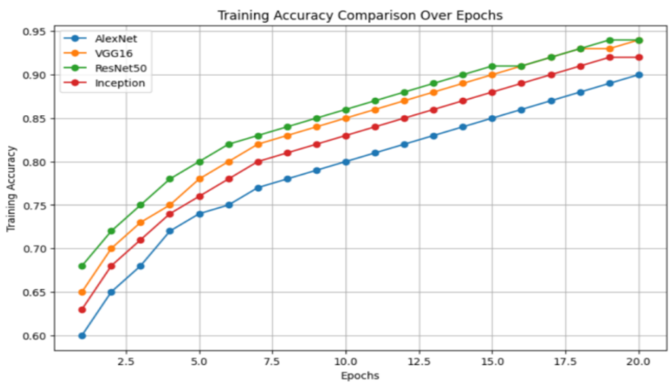

Fig 17 comparison of training accuracy of models

Comparing these models, it was found that Inception and ResNet50 dominate the others in terms of the quality of the pictures they reproduce. This can be attributed to their higher architectures that allow for deep and complex extraction of features. VGG16 is less sophisticated as a model but it functions effectively as a result of it being both deep and uniform. The architecture of CNNs has however evolved since the emergence of AlexNet even if it is left behind by relative newcomers.

D. Performance Analysis

Table 2. Comparison of proposed model accuracy with existing methods.

CLASSIFICATION METHOD	LEARNING MODEL	ACCURACY
Proposed method	AlexNet	0.85
	VGG16	0.88
	Inception	0.91
	ResNet50	**0.95**
Yadav et.al[15]	ORB and SVM	0.77
	VGG16	0.923
	INV3	0.875
	Caps Net	0.856
Rafidison et.al[16]	ImageNet	0.9199
Sharma et.al[17]	AlexNet	0.3612
	Resnet50	0.7810
	GoogleNet	0.7167
ian Seo & Kyung-shik Shin[18]	VGG16 H-CNN	0.9352
	VGG19 H-CNN	0.9333

From the table 2, it is clear that different classifiers as well as the learning paradigms have different accuracy levels on image recognition. For the proposed method the maximum accuracy score achieved is of the ResNet50 model which has given the value of 0. 95%. This again is higher compared to what we found in AlexNet which is 0. 85, VGG16 is 0. 88, and Inception model shows 0. 91 percentage of performance. This result is in tandem with the observation made by Yadav et al who obtained an accuracy of 0.923 for the VGG16 model. Implying that it has a capability of performing very well but not at the same level of efficiency as ResNet50. They also attempted other models including the ORB and SVM and obtained a score of 0. 77, INV3 with 0.875. However, in another study by Sharma et al, 2017 lower accuracies were achieved with the architectures; AlexNet (0. 3612), ResNet50 (0. 7810), and GoogleNet (0. 7167) acknowledging that the accuracy achieved may also depend on the implementation and the types of the used datasets. furthermore, in the more recent works, Ian Seo and Kyung-shik Shin's on hierarchical Convolutional neural networks (H-CNN) presented better results with VGG16 0.9352 And the best value of VGG19 H-CNN at 0.9333 . In conclusion, it can be said that ResNet50 is immune to the reduction in size and the models achieve the intended goal of obtaining high accuracy of classification.

V. IMPLICATIONS AND FUTURE WORK

It is evident that models with deeper and more complicated architecture, like ResNet50, are more appropriate for analyzing complex features, like the diagnosis of learning disabilities. The discovery that ResNet50 is the most effective model for predicting learning disabilities has important implications for educational psychology and special education. The model's high accuracy and robustness show how advanced deep learning techniques can be used as dependable tools for identifying learning disabilities at an early stage. This early detection can result in prompt and specific interventions, leading to significant improvements in educational outcomes for affected students. Furthermore, precise predictions enable the development of personalized learning plans, which enhance the overall learning experience and academic performance of students with learning disabilities. In addition, schools can utilize these tools to allocate resources and support services more efficiently, ensuring that students receive the necessary assistance without any unnecessary delays.

Future research should focus on Validating and enhancing the findings of this study by involving larger and more diverse datasets. This will ensure the generalizability of ResNet50 across different demographics and types of learning disabilities. Exploring ensemble learning techniques could also improve prediction accuracy by leveraging the strengths of multiple models.

Additionally, developing real-time implementation strategies for these models in educational settings could provide immediate feedback and support for students, making the technology more practical and usable [19]. Integrating image-based predictions with other data sources, such as academic records and behavioral assessments, could lead to more comprehensive diagnostic tools.

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