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A Novel Approach for Diagnosing Neuro-Developmental Disorders using Artificial Intelligence

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Abstract Artificial Intelligence (AI) has been rapidly advancing especially in the field of medicine. One of the highly considerable medical fields in the world today is that of neurodevelopment and diagnosing any disorders pertaining to the same can be overwhelming. Considering, the fact that neurodevelopment plays a significant role in the growth and nourishment of a child, the former sentence is an irony as parents wouldn't wish for their children to possess reduced capabilities in comparison to other children of the same age. In fact, testing the mental growth of a child is a tedious task that involves visiting the doctor each time and spending a lot of time. The proposition of this paper overcomes the above-mentioned hassles by utilizing computer-aided techniques for identifying neurodevelopmental disorder. The proposed framework has its foundation over mathematical and Deep Learning (DL) models which helps in the diagnosis of four varied neurodevelopmental disorders which often tend to occur in the early phases of a child's life. The application put forward here would suggest suitable remedies and strategies to parents and teachers that they can adopt to help their child recover from the illness.
Keywords: Artificial Intelligence (AI); Diagnosis; Healthcare; Neurodevelopmental Disorders (NDDs) Neural Network (NN).

1. Introduction

Artificial Intelligence (AI), one of the broadest sectors of Computer Science, is all about curating solutions and frameworks that solve problems that typically require human power with ease and efficiency. It truly involves a multidisciplinary approach especially due to the evolutionary changes being brought about by Machine Learning (ML) and Deep Learning (DL) models with a special focus on the medical industry [1]. The Neurodevelopmental disorder (NDD) is not a new jargon when looked at from the healthcare perspective and in recent years the term has become friendlier with AI. This paper introduces a DL-based system that learns from patterns and predicts the correct class to assist parents and/or teachers in the early and efficient detection of Neurodevelopmental disorders. Additionally, it places control of the system in the capable hands of parents, teachers, and/or carers through the use of a user interface designed as an Android application. This helps them support children who fall under the umbrella of neurodevelopmental disorders while providing them with professional assistance that can be accessed whenever necessary and, if used, may help gradually elicit a progressive performance in the child. The final idea lies in confining the conditions of a child diagnosed into capable hands that cater to their needs regularly.

After a whole lot of contemplation, the introduction so far leads to believe that developing an artificially intelligent algorithm to diagnose neurodevelopmental disorders is not beyond reach. Thus, the objectives of this paper are surmised within two aims. Foremost, a system that can categorize common NDD's in growing children and secondly offering the choice of a counsellor or psychologist, to assist in her/his upbringing. The only disclaimer remains that the methods of diagnosis offered are not in the confines of

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the author, but it has been taken after intensive research on the subject of NDDs and prevailing studies. Now, AI lends a helping hand to the field of NDD's in terms of recovery and rehabilitation. However, to impact the society on a positive note, the authors of this paper envision to utilizing AI-based expert systems that can contribute right from the diagnosis and prognosis of NDDs.

Neural networks are not a new concept, one of its types is the Recurrent Neural Network (RNN) which is fundamental, as the name suggests, recurrent, gives level zero inputs for a net which it retains in case a set of level one and subsequent inputs are shoved into the net as in figure 1. This involves the process of neural nets learning and apprehending from the previous inputs as well as prior inputs which was initially understood or learned. The main and obviously the most important feature of a Recurrent Neural Network is the Hidden state, which in essence can recall some statistics of a previously inputted sequence [2].

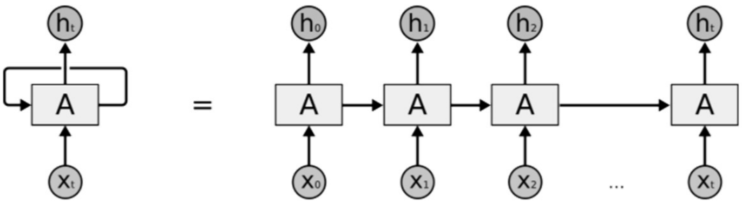

Figure 1. Structure of Unrolled RNN [6]

A classic and descent UI is bound to provide a user-friendly and comfortable user experience enabling a natural and intuitive feel while the user interacts and uses the software. In the case of an android app, the UI is developed through a layer of widgets and designs as shown in figure 2. The layouts, called View Group objects, are containers which control the viewing position of the screen [3]. On the other hand, widgets are objects such as buttons, textboxes, input fields, etc. Generally, the UI is defined on an xml file and the atomic unit of such applications is the activity.

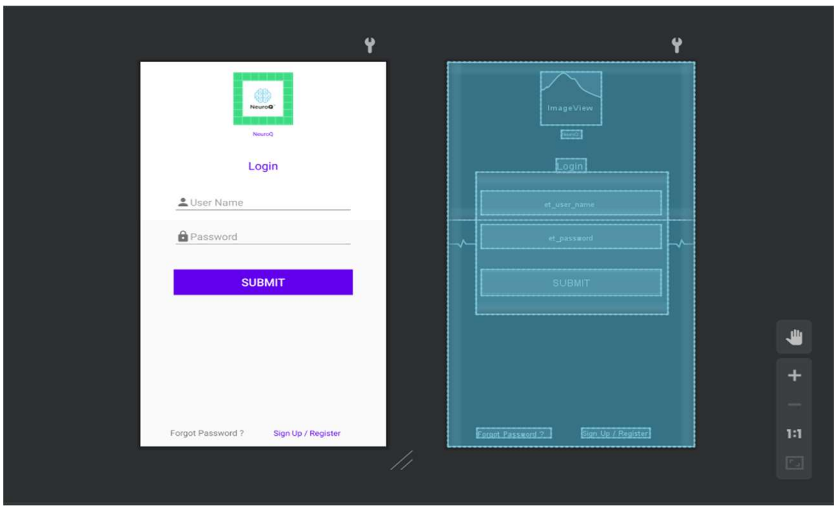

Figure 2. Android UI Design

The organization of this work is followed as: Section 2 discusses about related work. Section 3 discusses about our proposed work in detail. Further, Section 4 explains results of our simulation. Further, section 5 concludes this work in brief including some remarks for future research.

2. Related Work

Disorders of the brain that affect a child's development or upbringing fall under neurodevelopmental disorders. Studies done by the Adverse Childhood Experiences (ACE) have found that children suffering with NDDs can have difficulties in conversing, memorizing, learning, and even behaving. So, neurodevelopmental disorders basically mark brain disabilities and exhibit at the early ages in a child [4]. This background study discusses the transition of the diagnosis from traditional medical methods to a modern artificial intelligence assistance. Some of the well identified and prevalent NDDs are intellectual disability, dyslexia, autism, attention deficit hyperactivity disorder, learning deficits, and dyspraxia [5]. The evolution and growth of genetics and its impact on transforming the classification and detection of NDDs has been analysed by Crocq and Rosendahl. The generally observed pattern is to deviate away from the categorization of disorders as separate and individual entities and this happens due to the rising appreciation for the phenotypic overlap between the NDDs. Another possible area of exploration is to check whether the very same set of genes or functionally interlinked genes may be apprehended across NDDs [6]. NDDs are distinct in nature though the same categories behave the same when taking behaviours and outcomes into consideration [7]. Further moving to the study on how to get a computer to diagnose a neurodevelopmental disorder. Doernberg and Hollander noted differences in the diagnosis of NDDs as based in Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) and International Statistical Classification of Diseases and Related Health Problems, Tenth Revision(ICD-10) [8].

Now that the course traversed is down, the next step would be to see the reliance and relevance of AI where healthcare is concerned [9]. Shari Trewin analyses the obstructions faced by people with such disabilities and how they may be affected with the growing use of AI, ML, and DL. There is a stark difference in the fairness involved in people between a group of people with certain protected aspects of age/gender and a group of people suffering from certain disabilities [10]. There is a rich history and tradition of evaluating AI in healthcare. Even though past efforts can be learned from and build on best practices the doubt stays on the safety and effectiveness of AI that dynamically harnesses massive amounts of physiological records, and care delivery data from across healthcare systems. This was discussed by Magrabi, Ammenwerth, and McNair in their research findings on a historical perspective about the evaluation of AI in healthcare [11].

Second lastly the fact taken into consideration is that some of the earliest works done with AI for NDD is via functional and structural imaging of the brain i.e. the use of Magnetic Resonance Imaging (MRI) scans. Neuroimaging studies of middle-aged people having the developmental disorders gives a whole lot of information on the underlying abnormalities and thus effectuating the diagnosis of NDDs [12]. Attention-deficit/hyperactivity disorder (ADHD-200) shows that Functional magnetic resonance imaging (FMRI)-based diagnosis has the potential to assist psychiatrists in providing improved diagnosis and treatment for psychiatric patients. Structural and functional brain imaging and neuropsychological and neurophysiological markers may provide further dimensionality [13]. Duda, Haber, and Daniel used diverse ML algos to find best classifying features using Social responsiveness scale (SRS), they came up with an accuracy greater than 96 percent as well [14]. Studies done have also shown that Neurodevelopmental assessment consists of sensory motor and academic testing of more than 900 functions, so the idea is to stick with question answer slots to work on two model layers and determine whether a child has the NDD [15]. Initially though, Oppositional Defiant Disorder (ODD) had been counted as a much mild form of conduct disorder, but now it holds an independent position with other NDDs. Although it still stands along with other neural disorders with its etiology lying in temperament, cognitive skills and deficits and other physical factors [14]. Finally talking about the user interface which can assist in bridging the gap between persons and the computer aid. The database of preference is SQLite which is used to perform database operations on android devices such as storing, manipulating, or retrieving persistent data from the database [16]. Diving in thus with the thought that NDDs commonly occurs in industrialized countries and that figure as high as 15% of children are described as having NDDs and in Aboriginal children, the prevalence is often much higher, the aim is to reduce this percent as the children grow up.

3. Proposed Work

The design flow breaks the whole idea into modules of milestones to be achieved to reach the forementioned objectives. It makes the task of following through easy and neat. Figure 3 shows the process flow and the need to develop, import and ready the dataset for use. The next step is to build the individual models and train them, finally the frontend comes where the UI has to be built.

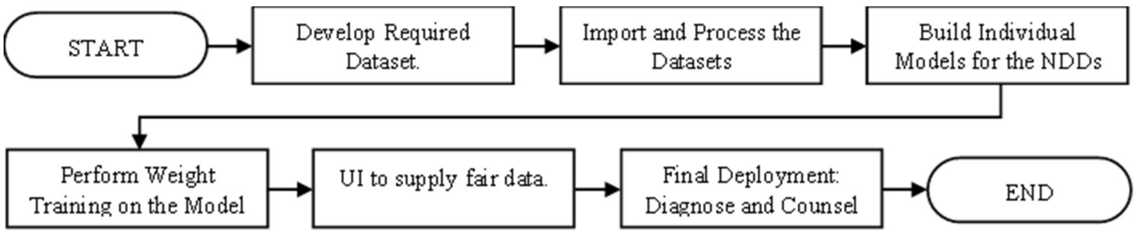

Figure 3. Process Flow

The implementation has been divided into two phases. The first is the deep learning phase consisting of individual model building for each of the four chosen specifications of neurodevelopmental disorders. The second phase entails the development of a user interface with a mathematical model for revision. Though before the second phase there is an intermediate phase of model conversion. Table 1 depicts the dimensions of the dataset used to train the models for each of the individual specifications. The table below gives the total entries in the csv files of each of the NDDs and the number of effective parameters that the model trains for. The class of NDD has not been taken into consideration, else the complete dimension for each can be calculated by:

$$Dimension = No.of\ Enteries\ x\ (Parameters + 1)$$

Table 1: Dataset Dimensional Influences

Specification	No of Entries	Training Parameters
Attention Deficit Hyperactive Disorder	1320	18
Autism Spectrum Disorder	1195	23

Developmental Coordination Disorder	1200	15
Oppositional Defiant / Conduct Disorder	1215	22

3.1 Phase I: Model Building

Many researchers or academician used the concept of neural networks in defining the backend. Running through the model building, the essence of deep learning lies in logistic regression. In research, the outcome needs to be either a yes or a no making it a binary problem thus facilitating the use of sigmoid function as the activation function in the output layer of the recurrent neural network [17]. Further, the activation within the hidden layers is the rectified linear unit, ReLU in short. ReLU being linear in nature makes it much easier to train models to achieve better performance. It is healthy for the hidden layer specifically since, it outputs the input for positive results and zero otherwise [18]. Moreover, to overcome some of the limitations of sigmoid, the ReLU was introduced hence explaining why the need is use two different activation functions in the same model. Sigmoid function and ReLU are of the form:

$$S(x) = \frac{1}{1+e^{-x}}$$

$$R(x) = \max(0, x)$$

Over to the use of optimizers and losses in the model. Adam is one of the optimization algorithms used for replacement in the case of stochastic gradient descent to train the DL models.
The enticing factor about Adam is that it combines the features of AdaGrad and RMSProp algorithms to provide an optimal algorithms which can deal with spurious gradients or noise issues [19]. Furthermore, the data split for training is 75%: 25% the test size goes to a certain extent in determining the accuracy as well. Now coming to losses in RNN LSTM models. Stochastic gradient descents are used to train the neural networks as entails the selection of a loss function during the process of designing and configuration of the model. There are several loss functions which can make it tedious and confusing to choose the right one in the right situation. Typically, with neural networks, aim is to minimize the error. The choice of the cost function is tightly coupled with the choice of output unit. The loss function used in building this model is 'MSE'. MSE, is calculated as the average of the squared differences between the predicted and actual values snapshot shown in figure 4. The result is always positive regardless of the sign of the predicted and actual values and a perfect value is 0.

Here, the Long Short-Term Memory (LSTM) is vitally helping our model remember its prior inputs and work on the inputs now pushed in [20]. LSTM works with whether it needs to keep a piece of information or get rid of it. A forget gate layer in the sigmoid is used '*ft*'. The information stored is, '*it*'. This updates the new state, '*Ct*' and then the state moves to the output. $ot = \sigma\ (Wo.\ [ht\text{-}1,\ xt] + bo)$ which is passed though the sigmoid gate, so only desired sections move to the output $ht = ot * \tanh\ (Ct)$

Finally, the final step before phase two is model conversion. Here, it is necessary to note that python saves its model in .h5 format which is not compatible with android development. Thus, a crucial step here is to convert the model from .h5 to android compatible, tfl.ite model [21]. Model conversion is a simple errand given that google colab exists. All the required modules are available without need for installation. Open a new python file on drive and follow with the pseudo-code given below where each action is given in purple, the variables are given in green, and the mathematical functions are in red. Once that the models have been converted, phase II is taken up which is to build the UI.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 8)                 152
_________________________________________________________________
dense_1 (Dense)              (None, 8)                 72
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 9
=================================================================
Total params: 233
Trainable params: 233
Non-trainable params: 0
_________________________________________________________________
None
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 8)                 192
_________________________________________________________________
dense_1 (Dense)              (None, 8)                 72
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 9
=================================================================
Total params: 273
Trainable params: 273
Non-trainable params: 0
_________________________________________________________________
None
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 8)                 128
_________________________________________________________________
dense_1 (Dense)              (None, 8)                 72
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 9
=================================================================
Total params: 209
Trainable params: 209
Non-trainable params: 0
_________________________________________________________________
None
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 8)                 184
_________________________________________________________________
dense_1 (Dense)              (None, 8)                 72
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 9
=================================================================
Total params: 265
Trainable params: 265
Non-trainable params: 0
_________________________________________________________________
None
```

Figure 4. Summary of the four models. Clockwise from top left: ADHD, Autism spectrum disorder (ASD), Developmental coordination Disorder (DCD) and Oppositional defiant disorder/ Obsessive-Compulsive Disorder (ODD/CD)

1. mount drive
2. import modules
3. assign directory and locate file
4. load the model from directory
5. setup the tflite converter using tf.lite.TFLiteConverter.from_keras_model
6. convert file from h5 to tflite
7. write tflite model to file

3.2 Phase II: User Interface

- To start with the application a registration page is prepared for the user.
- Users can proceed to login page after completing the registration.
- Use SQLite Database to store, manipulate and retrieve the data from Android.
- There are four specific buttons for four different disorders.
- To show the questions in a particular view, use the adapter class.
- Every disorder has different options. Each option carries a frequency code.
- It sums up the values according to the user's response.
- Every disorder has some standard value to check whether the child is suffering from it or not.
- Before showing the result, it checks twice. One via the math formula then through the DL model.
- To insert those models into the android studio it required tflite (Tensor Flow) extension.

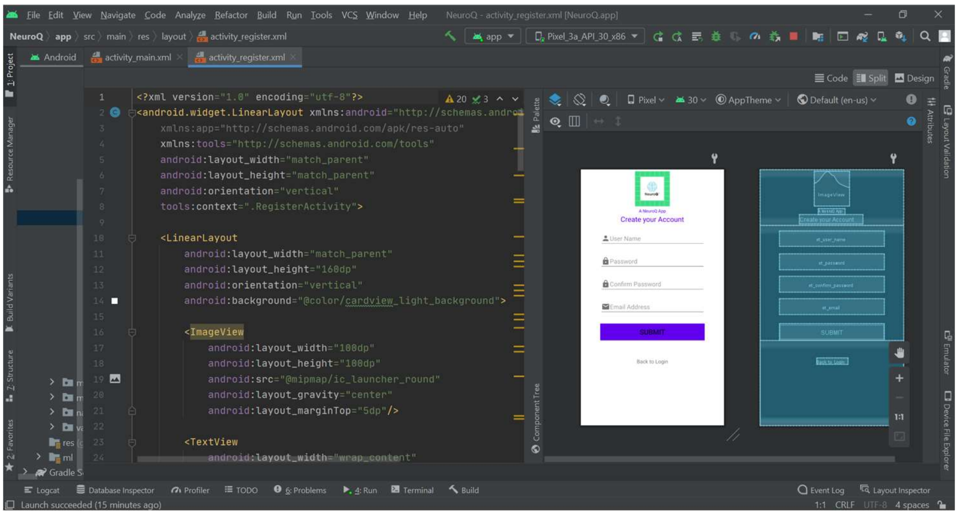

Figure 5. Initial Setup for User Interface

4. Simulation Results

Starting with the performance of the NDD models, the accuracy offered by each is above 0.90 and the number epoch increasing leads to a significant increase in performance. The activation function, optimizer and test size also affect the accuracy. The model losses calculation are given by the pseudo for MSE. Again, purple represents function, green represents variable, red represents mathematical calculations.

```
def MSE(actual, predicted):
        sum = 0.0
        for i in range(len(actual)):
                sum += (actual[i] - predicted[i])**2.0
        mse = 1.0 / len(actual) * sum
        return mse
```

MSE, as described earlier, is computed by calculating the average of the squared difference between the actual value and the predicted value. Squaring of the values lead to largely varied results having more error when compared to lower varied results. The graphs presented in Figure 6 shows the losses in the RNN models. Clockwise from top left: ADHD, ASD, ODD/CD, DCD.

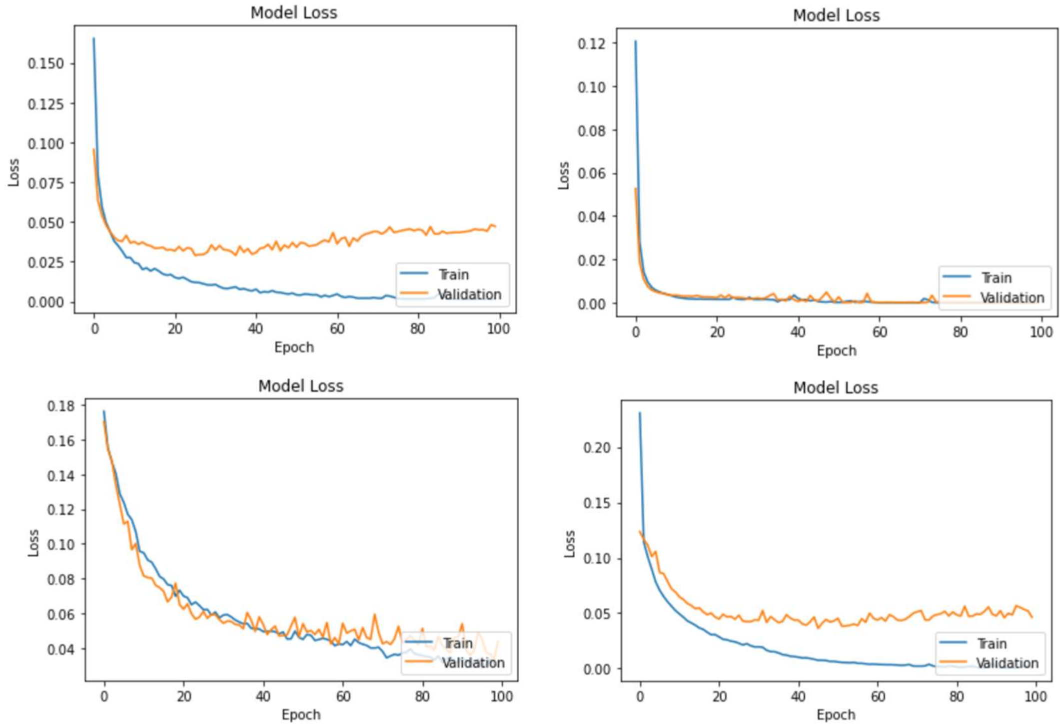

Figure 6. Model Losses in RNN

Confusion matrix will be used as the final deciding factor in terms of accuracy as shown in figure 7. This matrix has 4 main elements: True Positive (TP), False Negative (FN), True Negative (TN), and False Positive (FP) [22]. The figure below depicts the confusion matrices of the four specifications. What is aimed to increase, so as to affect the accuracy, are the divisions of True Positives and True Negatives.

$$\text{Accuracy: } \frac{TP+TN}{TP+FN+TN+F}$$

Predicted Values (ADHD)			
Actual Values (ADHD)		1	0
	Class 1	229	10
	Class 0	10	81

Predicted Values (ASD)			
Actual Values (ASD)		1	0
	Class 1	42	0
	Class 0	25	221

Predicted Values (DCD)			
Actual Values (DCD)		1	0
	Class 1	72	1
	Class 0	0	226

Predicted Values (ODD/CD)			
Actual Values (ODD/CD)		1	0
	Class 1	33	5
	Class 0	3	202

Figure 7. Confusion Matrices

Clockwise from top left, the confusion matrix of ADHD results in 229 true positives, the advantage here being only 20 values being predicted wrong, thus giving an accuracy score of 0.93, while the confusion matrix of ASD results in 221true negatives, the advantage here being only 25 values being predicted wrong, thus giving an accuracy score of 0.99, that of DCD results in 226 true negatives, the advantage here being only 1 value being predicted wrong, thus giving an accuracy score of 0.9. Finally, the confusion matrix of ODD/CD results in 33 true positives and 202 true negatives, the advantage here being only 8 values being predicted wrong, thus giving an accuracy score of 0.95.
Further, in each of the specifications the UI has a set of questions to be run through a mathematical model as given by the psychological research. Once done the results run through the LSTM to verify and finally output is sent to the user as a child with the symptoms of an NDD or not. It is necessary to keep in mind that the UI is specifically different for each of the specifications which is to say that the questions and calculation models for ADHD, ASD ,DCD and ODD/CD are each different and unique to themselves. ADHD and ODD/CD use the Vanderbilt Scale, ASD uses the Miriam Scale and DCD uses the Alberta CHF Scale.

A summary of all the mathematical values affecting the construction of the solely the model has been given in the table 2. Precision refers to the closeness of predicted values with respect to each other, recall is the rightly predicted true values of all positive values, while the F1 represents the balance between the precision and recall, kappa gives the reliability of values predicted and AUC is the area under the ROC curve [23].

Table 2. Models Results

	ADHD	**ASD**	**DCD**	**ODD/CD**
Accuracy	0.93	0.99	0.91	0.95
Precision	0.89	0.99	0.99	0.98
Recall	0.92	0.99	0.89	0.96
F1	0.89	0.99	0.94	0.97

Kappa	0.84	0.98	0.72	0.82
AUC	0.92	0.98	0.94	0.92

All the measures in table 2 are performance measures aiming to reflect the efficiency of final outcomes. In each of the cases, model can have an improved accuracy by virtue of increasing the number of epochs or changing the optimizer in the model.

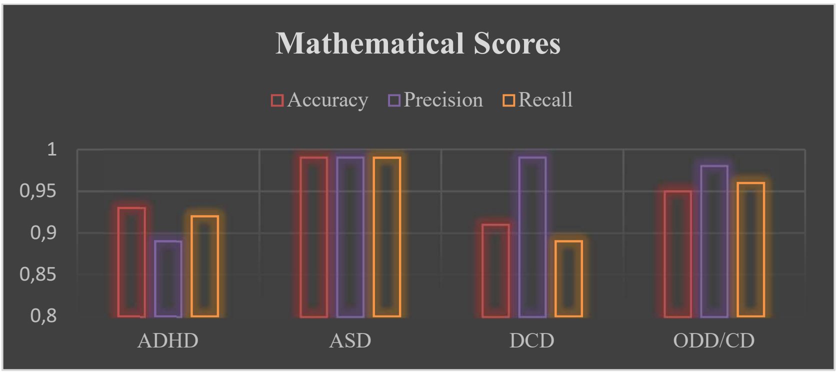

Figure 8. True Values for different Models

Hence, Changing the losses, test size and activation functions as well are some of the ways to tamper with accuracy. The chart in figure 8 compares the scores for each model.

5. Conclusion and Future Works

The proposed system aimed to use the general clinical functions to detect any abnormalities in the performance of children/teenagers. It has succeeded in doing so. Once the neurodevelopmental disorder is detected the severity was reviewed and accordingly guidance and advice were generated to suit the mental state of the said child in question. The algorithms to tackle outliers and the mathematical model have hit individual accuracies over 90%, with their sensitivity and specificity depending on the psychological aspects of questions based on research done previously. A child's brain development is always an utmost concern for parents and teachers, it determines the future undertakings of a child to a severely vast extent. Diagnosis in artificial intelligence thereby developing cognitive and emotional ability is a budding concept. But there is still much to discover.

Some of the facets of AI-based diagnosis are not ideal from a medical perspective but with rapidly improving and changing technology along with the implementations in a fast-paced and edgy world, elevations that have not long ago seemed beyond attainability can be looked forward to. And thus, the future scope of this project ranges from being able to diagnose NDD in children all the way to being able to define the degree of effect that it has on his / her daily functioning. The major future aspiration now relates to having a machine interpret the developmental issues where the brain is concerned and then if this sphere is well and better achieved the rest of whatever can be done beyond is all up to one's imagination. Including multiple other NDD specifications as well has been left to future endeavours.

Declaration of Competing Interest

The authors report no conflicts of interest.

References

[1] Baum, S.D. Artificial Interdisciplinary: Artificial Intelligence for Research on Complex Societal Problems. Philosophy and Technology, Vol. 34, 45-63(2020).

[2] Bo-Jian Hou and Zhi-Hua Zhou. Learning with Interpretable Structure from Gated RNN. IEEE transactions on neural networks and learning systems 31 (7), 2267-2279 (2020)

[3] Bianchi, J. Corbetta, L. Invernizzi, Y. Fratantonio, C. Kruegel and G. Vigna, What the App is That? Deception and Countermeasures in the Android User Interface, 2015 IEEE Symposium on Security and Privacy, 31-948(2015.

[4] Tracy L. Bale, Tallie Z. Baram, Alan S. Brown, Jill M. Goldstein, Thomas R. Insel, et. al. Early Life Programming and Neurodevelopmental Disorders, Biological Psychiatry, Vol. 68(4), 314-319 (2010).

[5] Taylor, Eric and Rutter, Michael. Classification. Rutter's Child and Adolescent Psychiatry. Wiley Online Books, 5th Edition Chapter 4 (2008).

[6] Morris-Rosendahl DJ, Crocq MA. Neurodevelopmental disorders-the history and future of a diagnostic concept. Dialogues in Clinical Neuroscience. Vol. 22(1):65-72 (2020).

[7] Bishop, Dorothy and Rutter, Michael. Neurodevelopmental Disorders: Conceptual Issues, Rutter's Child and Adolescent Psychiatry, Fifth Edition. 2-41(2008), Serial No. 9781405145497,

[8] Doernberg, E., & Hollander, E. Neurodevelopmental Disorders (ASD and ADHD): DSM-5, ICD-10, and ICD-11. CNS Spectrums, Vol.21(4), 295-299(2016).

[9] Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. Future Healthcare Journal. Vol.6(2):94-98(2019).

[10] Shari Trewin. AI Fairness for People with Disabilities: Point of View , Artificial Intelligence, 1-9(2018),

[11] Magrabi, F., Ammenwerth, E., McNair, J. B., De Keizer. Artificial Intelligence in Clinical Decision Support: Challenges for Evaluating AI and Practical Implications. Yearbook of medical informatics, 28(1), 128–134 (2019).

[12] Frith, Christopher, Frith, Uta. What Can We Learn from Structural and Functional Brain Imaging? Rutter's Child and Adolescent Psychiatry, , Wiley Online Books, Serial No. 9781444300895, 134-144(2021).

[13] Brown Matthew, Sidhu Gagan, Greiner Russell, Asgarian Nasimeh, Bastani Meysam, Silverstone Peter, Greenshaw Andrew, Dursun Serdar, ADHD-200 Global Competition: diagnosing ADHD using personal characteristic data can outperform resting state fMRI measurements, Frontiers in Systems Neuroscience Vol.6, 69 (2012).

[14] Duda, M., Haber, N., Daniels, J. et al. Crowdsourced validation of a machine-learning classification system for autism and ADHD. Translation Psychiatry 7(5), e1133 (2017).

[15] Lamsal, R., Dutton, D.J. & Zwicker, J.D. Using the ages and stages questionnaire in the general population as a measure for identifying children not at risk of a neurodevelopmental disorder. BMC Pediatr 18, 122 (2018).

[16] Simone Mutti, Enrico Bacis, and Stefano Paraboschi. SeSQLite: Security Enhanced SQLite: Mandatory Access Control for Android databases. In Proceedings of the 31st Annual Computer Security Applications Conference. Association for Computing Machinery, 411–420 (2015).

[17] Sridhar Narayan, The generalized sigmoid activation function: Competitive supervised learning, Information Sciences, Vol. 99(1), 1997, 69-82 (1997).

[18] Abien Fred Agarap. Deep Learning using Rectified Linear Units (ReLU). eprint 1803.08375, 7(2018).

[19] Z. Zhang, Improved Adam Optimizer for Deep Neural Networks. IEEE/ACM 26th International Symposium on Quality of Service (IWQoS), 1-2 (2018),

[20] F. A. Gers, J. Schmidhuber and F. Cummins, Learning to Forget: Continual Prediction with LSTM, Neural Computation, Vol. 12(10), 2451-2471(2000).

[21] Li Shuangfeng. TensorFlow Lite: On-Device Machine Learning Framework. Journal of

Computer Research and Development, Vol. 57(9): 1839-1853 (2020).

[22] A.M. HAY, The derivation of global estimates from a confusion matrix, International Journal of Remote Sensing, Vol. 9(8), 1395-1398(1988).

[23] Jesse Davis and Mark Goadrich. The relationship between Precision-Recall and ROC curves. In Proceedings of the 23rd International conference on Machine learning. Association for Computing Machinery, 233–240(2006).