

# DAYANANDA SAGAR UNIVERSITY

KUDLU GATE, BANGALORE – 560068



**Bachelor of Technology  
in  
COMPUTER SCIENCE AND ENGINEERING**

## **Major Project Phase-II Report**

### **“EARLY DETECTION OF DYSGRAPHIA”**

By

**Abhinav Manikanta J- ENG18CS0011**

**Abhishek B Kacher- ENG18CS0013**

**Adith Shivakumar- ENG18CS0017**

**Chandan R- ENG18CS0067**

**Under the supervision of**

**Dr. Revathi V**

**Associate Professor**

**Dept. of Computer Science and Engineering**

**DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING,  
SCHOOL OF ENGINEERING  
DAYANANDA SAGAR UNIVERSITY  
(2021-2022)**



**DAYANANDA SAGAR UNIVERSITY**

**School of Engineering**  
**Department of Computer Science & Engineering**  
Kudlu Gate, Bangalore – 560068  
Karnataka, India

## **CERTIFICATE**

This is to certify that the Phase-II project work titled “**EARLY DETECTION OF DYSGRAPHIA**” is carried out by **Abhishek B Kacher (ENG18CS0013)**, **Abhinav Manikanta J (ENG18CS0011)**, **Adith Shivakumar (ENG18CS0017)**, **Chandan R (ENG18CS0067)**, bonafide students of Bachelor of Technology in Computer Science and Engineering at the School of Engineering, Dayananda Sagar University, Bangalore in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Engineering, during the year **2021-2022**.

**Dr. Revathi V**

Associate Professor  
Dept. of CS&E,  
School of Engineering  
Dayananda Sagar University

**Dr Girisha G S**

Chairman CSE  
School of Engineering  
Dayananda Sagar University

**Dr. A Srinivas**

Dean  
School of Engineering  
Dayananda Sagar University

Date:

Date:

Date:

**Name of the Examiner**

**Signature of Examiner**

1.

---

2.

---

## DECLARATION

We, **Abhishek B Kacher (ENG18CS0013), Abhinav Manikanta J (ENG18CS0011), Adith Shivakumar (ENG18CS0017), Chandan R (ENG18CS0067)**, are students of the seventh semester B.Tech in **Computer Science and Engineering**, at School of Engineering, **Dayananda Sagar University**, hereby declare that the phase-II project titled “**EARLY DETECTION OF DYSGRAPHIA**” has been carried out by us and submitted in partial fulfillment for the award of degree in **Bachelor of Technology in Computer Science and Engineering** during the academic year **2021-2022**.

| Student                                    | Signature |
|--|-----------|
| <b>Abhishek B Kacher<br/>ENG18CS0013</b>   |           |
| <b>Abhinav Manikanta J<br/>ENG18CS0011</b> |           |
| <b>Adith Shivakumar<br/>ENG18CS0017</b>    |           |
| <b>Chandan R<br/>ENG18CS0067</b>           |           |
| <b>Place: Bangalore<br/>Date:</b>          |           |

## ACKNOWLEDGEMENT

It is a great pleasure for us to acknowledge the assistance and support of many individuals who have been responsible for the successful completion of this project work.

First, we take this opportunity to express our sincere gratitude to School of Engineering & Technology, Dayananda Sagar University for providing us with a great opportunity to pursue our Bachelor's degree in this institution.

We would like to thank **Dr. A Srinivas. Dean, School of Engineering & Technology, Dayananda Sagar University** for his constant encouragement and expert advice. It is a matter of immense pleasure to express our sincere thanks to **Dr. Girisha G S, Department Chairman, Computer Science, and Engineering, Dayananda Sagar University**, for providing the right academic guidance that made our task possible.

We would like to thank our guide **Dr. Revathi V, Associate Professor, Dept. of Computer Science and Engineering, Dayananda Sagar University**, for sparing her valuable time to extend help in every step of our project work, which paved the way for smooth progress and the fruitful culmination of the project.

We would like to thank our Project Coordinators **Dr. Meenakshi Malhotra** and **Dr. Bharanidharan N**, and all the staff members of Computer Science and Engineering for their support.

We are also grateful to our family and friends who provided us with every requirement throughout the course. We would like to thank one and all who directly or indirectly helped us in the Project work.

## TABLE OF CONTENTS

|   |       |
|---|-------|
| LIST OF ABBREVIATIONS .....             | vi    |
| LIST OF FIGURES .....                   | vii   |
| LIST OF TABLES .....                    | vii   |
| ABSTRACT .....                          | viii  |
| CHAPTER 1 INTRODUCTION.....             | 1     |
| 1.1. PURPOSE AND PROCESS .....          | 2     |
| 1.2. SCOPE.....                         | 3     |
| CHAPTER 2 PROBLEM DEFINITION .....      | 4-5   |
| CHAPTER 3 LITERATURE SURVEY.....        | 6-9   |
| CHAPTER 4 PROJECT DESCRIPTION.....      | 10-11 |
| 4.1. PROPOSED DESIGN .....              | 11    |
| 4.2. ASSUMPTIONS AND DEPENDENCIES.....  | 11    |
| CHAPTER 5 REQUIREMENTS .....            | 12-14 |
| 5.1. FUNCTIONAL REQUIREMENTS .....      | 13    |
| 5.2. NON-FUNCTIONAL REQUIREMENTS.....   | 13    |
| 5.3. SOFTWARE REQUIREMENTS.....         | 13    |
| 5.4. HARDWARE REQUIREMENTS.....         | 14    |
| CHAPTER 6 METHODOLOGY .....             | 15-18 |
| 6.1. DATA PREPROCESSING.....            | 16    |
| 6.2. CONVOLUTIONAL NEURAL NETWORKS..... | 16-17 |
| 6.3. RESNET.....                        | 18    |
| CHAPTER 7 EXPERIMENTATION .....         | 19-20 |
| CHAPTER 8 TEST AND RESULTS .....        | 21-24 |
| CHAPTER 9 CONCLUSION .....              | 25-26 |
| CHAPTER 10 FUTURE WORK.....             | 27-28 |
| REFERENCES .....                        | 29    |
| APPENDIX A .....                        | 30-31 |
| PAPER PUBLICATIONS DETAILS .....        | 32    |

## LIST OF ABBREVIATIONS

|          |                               |
|----------|-------------------------------|
| SVM      | Support Vector Machine        |
| CNN      | Convolutional Neural Networks |
| OCR      | Optical Character Recognition |
| RF       | Random Forest                 |
| AdaBoost | Adaptive Boosting             |

## LIST OF FIGURES

| Fig. No. | Description of the figure   | Page No. |
|----------|-----------------------------|----------|
| 1        | Proposed Block Diagram      | 11       |
| 2        | Neural Network architecture | 11       |
| 3        | CNN Architecture            | 17       |
| 4        | Data Augmentation           | 20       |
| 5        | Model Training              | 20       |
| 6        | Model Output                | 22       |
| 7        | Application Splash Screen   | 23       |
| 8        | Application Home Screen     | 23       |
| 9        | Dysgraphic Handwriting Test | 24       |
| 10       | Bad Handwriting Test        | 24       |
| 11       | Good Handwriting Test       | 24       |

## LIST OF TABLES

| Table No. | Description of the table | Page No. |
|-----------|--------------------------|----------|
| 1         | Test and Results         | 22       |

## **ABSTRACT**

Dysgraphia, a disorder affecting the written expression of symbols and words, negatively impacts the academic results of pupils as well as their overall well-being. The use of automated procedures can make dysgraphia testing available to larger populations, thereby facilitating early intervention for those who need it. Machine learning approach is employed to identify handwriting deteriorated by dysgraphia. To achieve this goal, a new handwriting dataset is collected consisting of several handwriting tasks and extracted broad range of features to capture different aspects of handwriting. These were given to a machine learning algorithm to predict whether handwriting is affected by dysgraphia.



# **CHAPTER 1: INTRODUCTION**

## **CHAPTER 1: INTRODUCTION**

The goal of this project is to build a machine learning model, which uses data-driven methods to detect dysgraphia. The purpose is to chalk out the characteristics of the people suffering from dysgraphia and characteristics related to the disease and detect the disorder as early as possible. Early detection enables children to seek help and improve their writing sooner and helps teachers adapt their teaching style after properly diagnosing a source of learning difficulty in a child.

### **1.1. PURPOSE AND PROCESS**

Writing is a skill developed in early childhood that is vitally important for learning as well as activities of daily living, particularly as academic and environmental demands increase with age. Dysgraphia and disorders of written expression, though relatively common in children, can be mistaken or overlooked by the school and family of the affected individual. Dysgraphia can be very depressing and painful for the person. Affected people would feel different from others and this can affect their self-esteem and have a negative effect on their academics.

The goal of this project is to build a machine learning model, which uses data-driven methods to detect dysgraphia. The objective of this model is to help the affected children to get treatment for the disorder as soon as possible to improve quickly, so that their academic life doesn't get affected and keep them mentally strong. If this model is used in hospitals for diagnosing, the chances of early detection is higher. So, detection of dysgraphia at early stages can be really helpful for the child and parents and the doctors. If therapy is given at early stages, earlier recovery is possible. So, this model is created to detect dysgraphia and help children suffering from this disorder.

## **1.2. SCOPE**

This project helps so many dysgraphia affected children by early detection of the disorder. The objective of this model is to help the affected children to get treatment to the disorder as soon as possible to improve quickly, so that their academic life doesn't get affected and keep them mentally strong. If this model is used in hospitals for diagnosing, the chances of early detection is higher. So, this project has a higher scope.

## **CHAPTER 2: PROBLEM DEFINITION**

## **CHAPTER 2: PROBLEM DEFINITION**

With dysgraphia, kids or adults have a harder time planning and executing the writing of sentences, words, and even individual letters. It's not that you don't know how to read, spell, or identify letters and words. Instead, your brain has problems processing words and writing. Dysgraphia can be very depressing and painful for the person. Affected people would feel different from others and this can affect their self-esteem and have a negative effect on their academics. So, detection of dysgraphia at early stages can be really helpful for the child and parents and the doctors. If therapy is given at early stages, earlier recovery is possible. So, this model is created to detect dysgraphia and help children suffering from this disorder.

## **CHAPTER 3: LITERATURE REVIEW**

## CHAPTER 3: LITERATURE REVIEW

According to the paper Identifying Developmental Dysgraphia Characteristics Utilizing Handwriting Classification Methods (2017) [1], Dysgraphia is a disturbance or difficulty in the production of written language related to the mechanics of writing. The difficulties manifest as inadequate performance of handwriting among children who have at least an average intelligence level and who have not been identified as having any obvious neurological or perceptual- motor problems. The prevalence of handwriting difficulties among elementary school students ranges from 10% to 34%. Dysgraphia can have profound implications for the individual in terms of compromised self-image and success in school. The aim of this study was to develop and test a statistical model for differentiating between dysgraphia and proficient handwriting based on their performance characteristics. This study focused on identifying and characterizing dysgraphia among Hebrew writing children. The SVM classifier shows accurate predictions for 89 out of 99 writing products, which leads to an accuracy of 89.9%.

According to the paper Dysgraphia detection through machine learning (2020) [2], a new handwriting dataset was collected which consisted of several handwriting tasks and a broad range of features were extracted to capture different aspects of handwriting. Those were fed to a machine learning algorithm to predict whether handwriting is affected by dysgraphia. Then they compared several machine learning algorithms and found that the best results were achieved by the adaptive boosting (AdaBoost) algorithm. The results have shown that machine learning can be used to detect dysgraphia with almost 80% accuracy, even while dealing with a heterogeneous set of subjects differing in age, sex and different hand usage. Subjects with any hand injury or physical indisposition to write were excluded. Velocity, jerk, acceleration, pressure, azimuth and altitude were first extracted in the form of a vector of the same length as the handwriting sample record. Classifier validation was conducted using stratified tenfold cross-validation, and the whole process was repeated ten times. Classification accuracy, sensitivity, and specificity over the ten repetitions were averaged. Results showed it is possible to

discriminate between dysgraphia and non-dysgraphic children with 79.5% accuracy on a sample of children of different ages using the AdaBoost algorithm and to a similar extent using the RF and SVM algorithms. The accuracy scores of the other two models were also quite high, 72.5% for SVM and 72.3% for RF classifier.

According to the paper, TestGraphia, a Software System for the Early Diagnosis of Dysgraphia (2020) [3], this study suggests an evaluation protocol for BHK test by including handwriting features such as writing size, non-aligned left margin, skewed lines, insufficient space between words, sharp angles, broken links between letters, collision between two letters, irregular size of letters, inconsistent height between letters with and without extension, atypical letters, ambiguous letters, traced letters, unstable track. These features should be considered by doctors and tools to diagnose dysgraphia. Certain features are closely geometry- based, while other features require a doctor's interpretation and some features can be automated.

According to the paper, Deep Learning Approach to Automated Detection of Dyslexia-Dysgraphia (2020) [4], it uses a modified version of convolution neural networks with keras using tensor flow backend, an OCR model was built using CNN. The overall accuracy of  $(86.14 \pm 1.02) \%$  is computed using the accuracy values of 87.18% and 85.12% from the train/test split and the cross-validation experiments. 5-Fold cross validation approach was used. In each trial, the accuracy value was calculated for each round and the final accuracy was calculated using the average values of all the rounds. In another study, Towards Detecting Dyslexia in Children's Handwriting Using Neural Networks (2019) [5], a similar approach was used using CNN along with keras and TensorFlow without OCR which led to an accuracy of 55.7%. So, the OCR model using CNN is preferred.



According to the paper, Image Classification using SVM and CNN (2020) [6], SVM model that used a very small dataset achieved an accuracy of 93% and although SVM is a very strong technique, achieving such a high accuracy was still an anomaly. Using data augmentation, the size of the dataset was more than tripled and was performed on SVM again, it achieved an accuracy of 82%. On successfully implementing CNN, it achieved an accuracy of 93.57% on the same dataset. So, it concludes that using CNN over large augmented dataset of images is better than using SVM because it provides higher accuracy.

## **CHAPTER 4: PROJECT DESCRIPTION**

## CHAPTER 4: PROJECT DESCRIPTION

### 4.1 PROPOSED DESIGN

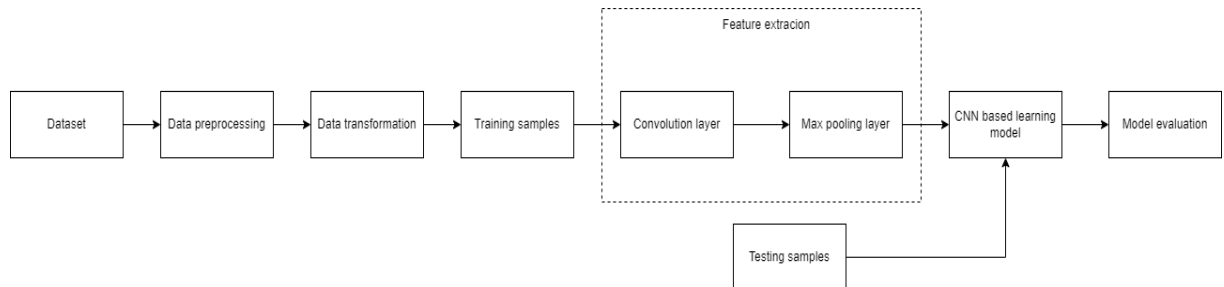


Fig.1: Proposed Design

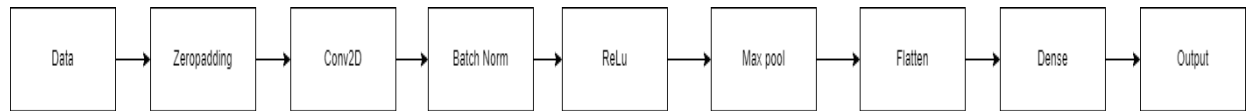


Fig.2: Neural Network architecture

The development of the dysgraphia prediction model begins with collection the data. The pre-processing phase is a phase before the training and testing of data where the collected data is tailored to meet the requirements. The dataset is now split into a training set and a testing set. Then, by applying the deep learning algorithms, the model is trained using the training set and later on test it on the testing set.

### 4.2 ASSUMPTIONS AND DEPENDENCIES

- The website requires a stable network connection.
- The user must have a good quality camera.
- The website will always be used on operating systems and browsers that have enough performance.

## **CHAPTER 5: REQUIREMENTS**

## **CHAPTER 5: REQUIREMENTS**

### **5.1 FUNCTIONAL REQUIREMENTS**

- The project should get the input in image format
- It should be able to detect dysgraphia after getting the test case input by comparing it with the trained model using machine learning.
- It should not falsely identify bad handwriting as dysgraphia.

### **5.2 NON-FUNCTIONAL REQUIREMENTS**

- The system must not lead to inaccurate results as it can lead to bad diagnosis.
- The prediction should take the minimum time possible to make the predictions.
- This model should be effective at analyzing dysgraphia disorder.
- The implementation must provide easy availability, correctness, flexibility and usability to the user to achieve above mentioned specific goals with effectiveness, efficiency and satisfaction.

### **5.3 SOFTWARE REQUIREMENTS**

- Jupyter notebook / Google Colab
- Python3 or above
- Visual Studio Code

## **5.4 HARDWARE REQUIREMENTS**

- 8 GB RAM and above recommended.
- 256 GB internal storage and above recommended.
- Intel core i3 processor and above.
- Ryzen 3 processor and above recommended

## **CHAPTER 6: METHODOLOGY**

## **CHAPTER 6: METHODOLOGY**

### **6.1. DATA PREPROCESSING:**

Data preprocessing is the process of transforming raw data into an understandable format. It is also an important step as working with raw data is not possible. The quality of the data should be checked before applying machine learning or data mining algorithms. Since less data is available, preprocessing techniques such as data augmentation is used.

Data augmentation: It is the process of modifying, or “augmenting” a dataset with additional data. This additional data can be anything from images to text, and its use in machine learning algorithms helps improve their performance. It is a strategy that enables practitioners to significantly increase the diversity of data available for training models, without actually collecting new data.

Data augmentation techniques such as cropping, padding, and horizontal flipping are commonly used to train large neural networks.

### **6.2. CONVOLUTION NEURAL NETWORKS:**

Convolutional neural networks (CNN) is a feed-forward artificial neural network. It has convolutional layers that have taken the role of feature extraction. Artificial neural network (ANN) based fully connected layers follow the classification process in a model. Fully connected layers contain multiple nodes and each node is connected to all of the next nodes of the next FC layer. Working with small size visual data, needed less number of neural nodes and in that case, can use only fully-connected layer blocks. In the case of a large image, more parameters needed to execute the process with an artificial neural network. CNN contains neural nodes connected to a small region of neurons of the next convolutional layer. It compares the given visual data with a specific part by part. This specific part is called a feature of the image. The convolutional layer at first lines up the feature from the input images and multiply each input image pixel by the corresponding feature pixel. Then perform summation of the pixel values and divide by the number of the total pixel in the feature.



The calculated values are put in the feature map and move the filter throughout the entire image. All the calculated values are reserved in the feature map. In this way, all features go through the process and generate different feature maps. The equation to obtain the convolutional layer is the following.

$$u_{ijm} = \sum_{k=0}^{K-1} \sum_{p=0}^{H-1} \sum_{q=0}^{H-1} z_{i+p,j+q,k}^{(l-1)} p_{qkm} + b_{ijm}$$

Where bias is commonly set as which does not depend on the position of the pixel of the image. as an identical value of weight. Activation function Rectified linear Unit (ReLU) taken part now and remove all negative values from the feature map and replace it with zero. The activation ReLU function formula is

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

In the pooling layer part, Max pooling layer shrinks the input image size by pooling the maximum value from the feature map, generated by the convolutional layer. The obtained equation of max-pooling layer,

$$u_{ijk} = \max_{p,q \in P_{i,j}} z_{pqk}$$

Here, define a set of pixels including the area. A pixel value, is gained by using pcs of pixel value with every channels. Finally, the fully connected layer converts the shrink images that come from the last pooling layer of the model, converting them to a single list array vector. The classification task is executed in the fully connected layer.

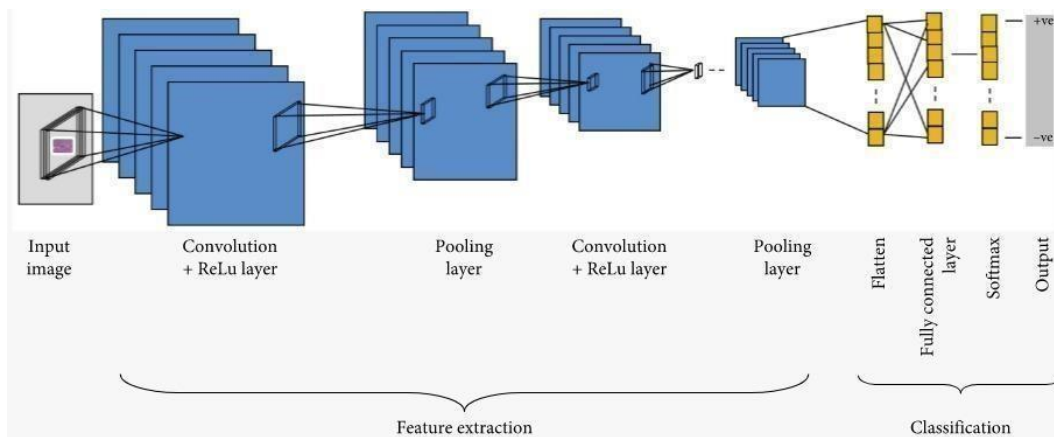


Fig 3: CNN

### **6.3. RESNET:**

Transfer learning in the machine learning field is a concept where the gained knowledge is transferred to another model to solve another related problem. Deep CNN based applications of Keras are trained with the ImageNet dataset. ImageNet project which is a large visual database design for visual object recognition research. Deep convolutional neural network-based models are trained with millions of images with thousands of classes.

The parameters of features gained by the model are transferable. Using the pre-trained weights in a new model can solve related problems more effectively than general models. The final block of the Keras applications contains dense layers for classification tasks.

A residual neural network (ResNet) is an artificial neural network (ANN). Residual neural networks utilize skip connections, or shortcuts to jump over some layers. Typical ResNet models are implemented with double- or triple- layer skips that contain nonlinearities (ReLU) and batch normalization in between. An additional weight matrix may be used to learn the skip weights; these models are known as HighwayNets. Models with several parallel skips are referred to as DenseNets.

## **CHAPTER 7: EXPERIMENTATION**

## CHAPTER 7: EXPERIMENTATION

- As there was a little dataset, data augmentation is performed on the data to increase the number of datasets.
- CNN was used with a train test split with 60% data for training and 40% for testing.
- It resulted in 49% accuracy.
- Since CNN resulted in low accuracy Resnet model was used to improve accuracy.
- Then, 78% accuracy was achieved.

```
def augment_data(file_dir, n_generated_samples, save_to_dir):
    print(listdir(file_dir))

    data_gen = ImageDataGenerator(rotation_range=10,
                                   width_shift_range=0.1,
                                   height_shift_range=0.1,
                                   shear_range=0.1,
                                   rescale=1./255,
                                   brightness_range=(0.3, 1.0),
                                   vertical_flip=True,
                                   fill_mode='nearest')

    for filename in listdir(file_dir):
        image = cv2.imread(file_dir + '/' + filename)
        image = image.reshape((1,)+image.shape)
        save_prefix = 'aug_' + filename[:-4]
        i=0
        for batch in data_gen.flow(x=image, batch_size=1, save_to_dir=save_to_dir, save_prefix=save_prefix, save_format='jpg'):
            i += 1
            if i > n_generated_samples:
                break
```

Fig 4: Data Augmentation

```
In [8]: model = Sequential([
        Conv2D(32, (3,3), activation = 'relu', input_shape = (240, 240, 3)),
        MaxPooling2D((2,2)),

        Conv2D(32, (3,3), activation = 'relu'),
        MaxPooling2D((2,2)),

        Flatten(),
        Dense(64, activation = 'relu'),
        Dense(1, activation = 'sigmoid')
    ])

In [9]: model.compile(loss = 'binary_crossentropy', optimizer = 'adam', metrics = ['accuracy'])

In [10]: model.fit(X_train, y_train, epochs = 10, batch_size = 32)

Epoch 1/10
44/44 [=====] - 20s 441ms/step - loss: 0.8001 - accuracy: 0.6078
Epoch 2/10
44/44 [=====] - 19s 442ms/step - loss: 0.5373 - accuracy: 0.7233
Epoch 3/10
44/44 [=====] - 20s 452ms/step - loss: 0.5322 - accuracy: 0.7262
Epoch 4/10
44/44 [=====] - 20s 452ms/step - loss: 0.3949 - accuracy: 0.8279
Epoch 5/10
44/44 [=====] - 20s 450ms/step - loss: 0.3242 - accuracy: 0.8519
Epoch 6/10
44/44 [=====] - 20s 443ms/step - loss: 0.2949 - accuracy: 0.8758
Epoch 7/10
44/44 [=====] - 19s 441ms/step - loss: 0.2115 - accuracy: 0.9237
Epoch 8/10
44/44 [=====] - 19s 443ms/step - loss: 0.1622 - accuracy: 0.9405
Epoch 9/10
44/44 [=====] - 19s 440ms/step - loss: 0.0941 - accuracy: 0.9673
Epoch 10/10
44/44 [=====] - 20s 452ms/step - loss: 0.0641 - accuracy: 0.9898

Out[10]: <keras.callbacks.History at 0x187a155e310>
```

Fig 5: Model Training

## **CHAPTER 8: TEST AND RESULTS**

## CHAPTER 8: TEST AND RESULTS

Table 1: Test and results

| SL NO | TEST CASES                   | RESULT   |
|-------|------------------------------|--|
| 1.    | Dysgraphic Handwriting Image | Predicts the image as dysgraphic with accuracy       |
| 2.    | Good Handwriting Image       | Predicts the image as good handwriting with accuracy |
| 3     | Bad Handwriting Image        | Predicts the image as bad handwriting with accuracy  |

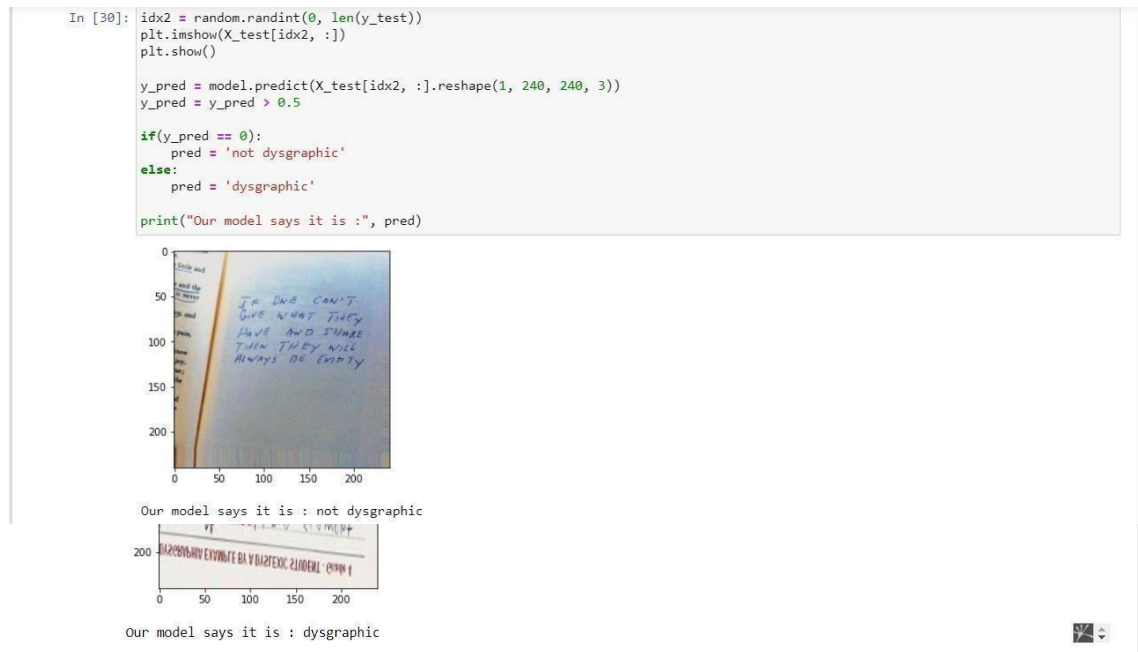


Fig 6: Model Output



Fig.7: Splash screen

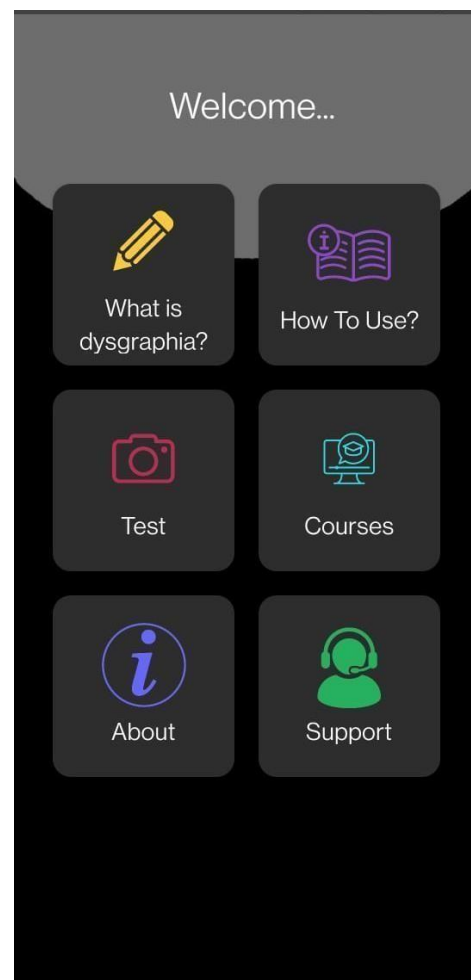


Fig.8: Home screen

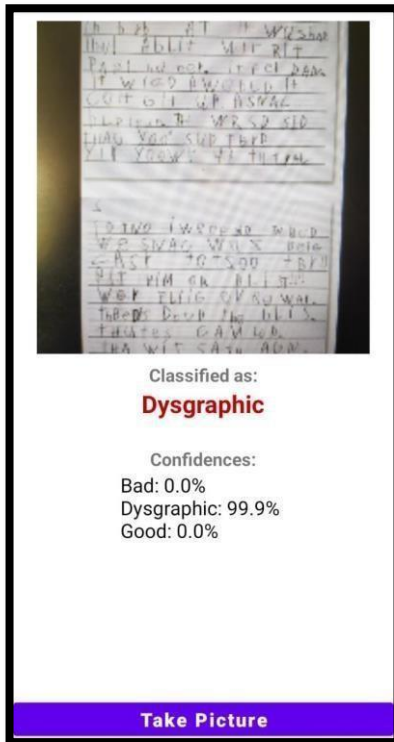


Fig.9. Dysgraphic handwriting test

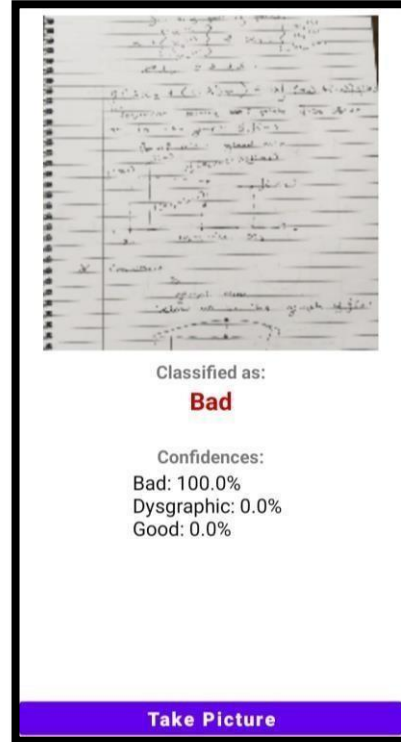


Fig.10. Bad handwriting test

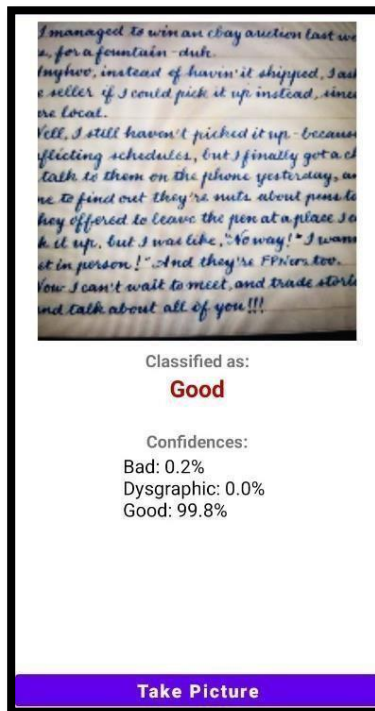


Fig.11. Good handwriting test



## **CHAPTER 9**

## **CONCLUSION**

## **CHAPTER 9: CONCLUSION**

Clearly dysgraphia is a hindrance for learning and improving in education. There is medicament that help to destroy those obstacles using technology, guidance, and support. CNN architecture is put forward for bad, dysgraphic and good handwriting detection with an objective of high classification accuracy. A genuine dataset was collected for the training and testing process which went smoothly. A training strategy comprised training model on the desirable patterns.

## **CHAPTER 10**

# **FUTURE WORK**

## **CHAPTER 10: FUTURE WORK**

- Different deep learning algorithms to increase the accuracy of our model.
- Doctor consultancy can be included through the application which helps the disorder students to take treatment easily.
- More courses will be added in the application for the students to improve their disorder.
- As of now, as there were very less datasets, in the future more data sets will be collected for increasing accuracy.
- Our application User Interface will be improved and security features will be provided.

## REFERENCES

1. *Rosenblum, Sara; Dror, Gideon (2017). Identifying Developmental Dysgraphia Characteristics Utilizing Handwriting Classification Methods. IEEE Transactions on Human-Machine Systems, 47(2), 293–298[1]*
2. *Peter Drotar and Marek Dobes (2020) Dysgraphia detection through machinelearning [2]*
3. *Giovanni Dimauro(2020) TestGraphia, a Software System for theEarly Diagnosis of Dysgraphia[3]*
4. *Pratheepan Yogarajah, Braj Bhushan(2020) Deep LearningApproach to Automated Detection of Dyslexia-Dysgraphia[4]*
5. *K. Spoon, D. Crandall and K. Siek. “Towards Detecting Dyslexia in Children’s Handwriting Using Neural Networks.”International Conference on Machine Learning AI for Social GoodWorkshop, 2019[5]*
6. *Koteswara Rao Pandi, Ipseeta Nanda (2020), Image Classificationusing SVM and CNN[6]*

## APPENDIX A

### DATA AUGMENTATION

```
def hms_string(sec_elapsed):
    h = int(sec_elapsed / (60 * 60))
    m = int((sec_elapsed % (60 * 60)) / 60)
    s = sec_elapsed % 60
    return f"{h}:{m}:{round(s,1)}"

def augment_data(file_dir, n_generated_samples, save_to_dir):
    print(listdir(file_dir))

    data_gen = ImageDataGenerator(rotation_range=20,
                                   width_shift_range=0.2,
                                   height_shift_range=0.2,
                                   shear_range=0.2,
                                   zoom_range = 0.2,
                                   vertical_flip=True,
                                   fill_mode='nearest')

    for filename in listdir(file_dir):
        image = cv2.imread(file_dir + '/' + filename)
        image = image.reshape((1,)+image.shape)
        save_prefix = 'aug_' + filename[:-4]
        i=0
        for batch in data_gen.flow(x=image, batch_size=1, save_to_dir=save_to_dir,
save_prefix=save_prefix, save_format='jpg'):
            i += 1
            if i > n_generated_samples:
                break;
```

## RESNET15v2

```
train_data_dir = 'dataset/train/'
test_data_dir = 'dataset/test/'

class_labels = os.listdir(train_data_dir)
print(class_labels)

for wdir in os.listdir('dataset'):
    print(wdir)
    wdir_total = 0
    for label in class_labels:
        total = len(os.listdir(os.path.join('dataset', wdir, label)))
        print(label, total)
        wdir_total += total
    print(wdir, '---- ', wdir_total)

resnet_model = tf.keras.applications.ResNet152V2(include_top=False,
                                                weights="imagenet",
                                                input_tensor=None,
                                                input_shape=(256,256,3),
                                                pooling="max",
                                                classes=1000)

resnet_model.trainable = False

inputs = resnet_model.input

m = tf.keras.layers.Dense(1024, activation='relu')(resnet_model.output)

outputs = tf.keras.layers.Dense(3, activation='softmax')(m)

resnet_model = tf.keras.Model(inputs=inputs, outputs=outputs)
```

## GITHUB REPOSITORY LINK:

<https://github.com/Kacher-Abhi/dysdoc>

## **PUBLISHED PAPER DETAILS**

### **International Research Journal of Engineering and Technology (IRJET)**

- Paper Title: Early Detection of Dysgraphia Using Convolutional Neural Networks
- Status: Accepted and Published
- Published Date: 24<sup>th</sup> May 2022
- Volume: Volume 9, Issue 5, May 2022
- Authors: Abhishek B Kacher, Abhinav Manikanta J, Adith Shivakumar, Chandan R
- Paper ID: FTP9052325
- Website Link: [Early Detection of Dysgraphia using Convolutional Neural Networks](#)









# EARLY DETECTION OF DYSGRAPHIA USING CONVOLUTIONAL NEURAL NETWORKS

Abhishek B Kacher<sup>1</sup>, Abhinav Manikanta J<sup>2</sup>, Adith Shivakumar<sup>3</sup>, Chandan R<sup>4</sup>

<sup>1,2,3,4</sup>Department of Computer Science and Engineering, Dayananda Sagar University, Bangalore, Karnataka, India

\*\*\*

**Abstract** - Handwriting is a complex ability to get and it demands lot of preparation and effort to be learnt. Children having dysgraphia exhibit troubles to write. This can cause tension and can otherwise impact instruction. drawing and sketching. It requires the close connection and arrangement of psychomotor and biomechanical processes. Dysgraphia is a difficulty in writing that straightforwardly impacts a student's talent to perform capably. Although dysgraphia is exactly elucidated as "distressing novel," it too influences a person's capability to envision and draw lines and shapes. There may lie a number of students that would benefit from proper understanding of this disorder by educators. This record of what happened is created to comprehend the condition of dysgraphia.

Dysgraphia, a disorder moving the inscribed verbalization of symbols and dispute, otherwise impacts the academic results of pupils in addition to their overall welfare. The use of automated processes can form dysgraphia experiments convenient to larger populace, through expediting early invasion for those who need it. We are working on a machine intelligence approach to recognize script run-down by dysgraphia. To achieve this aim, we composed a new script dataset incorporating several longhand tasks and elicited a broad range of visage to capture various aspects of manuscript. These were likely a machine intelligence invention to predict whether scrawl is impressed by dysgraphia.

## 1.1 DYSGRAPHIA

Dysgraphia is a disorder that makes learning difficult. Generally reviewed in modern articles within the circumstances of calligraphy and orthography, dysgraphia exactly translates to troublesome literature. Viewed widely as a script deterioration, dysgraphia also influences a person's strength to draw shapes and to draw lines. The condition shows a neurocognitive disorder guide executive functioning and fine- engine and visual-engine shortfalls. The syndromes of dysgraphia are frequently missed by educators, and undergraduates accompanying the condition are viewed as uninspired or indifferent.

Teachers bear to see the signs and syndromes of dysgraphia and not remove from job a minor as utterly bearing messy manuscript. If a faculty member starts to visualize a trend of indecipherable articles, it is appropriate for the bureaucracy to question whether this child has dysgraphia. Teachers bear note that parts of the document process are most troublesome for the minor. While dysgraphia frequently happens in addition to another disadvantage, many pupils accompanying dysgraphia can exhibit extreme academic realizations in additional issues. Figure 1 shows an instance of the handwriting of a second-grade pupil accompanying dysgraphia, and a usual second grader's scrawl. The traits of dysgraphia are different and juniors can exhibit some individual or more of these traits.

**Key Words:** Dysgraphia, Handwriting, CNN

## 1.INTRODUCTION

Handwriting is an essential ability, because children give up to 60% of their opportunity at school writing. Appropriately neat and robotic script is necessary for the purchase of added bigger-order skills to a degree of orthography and story arrangement. Handwriting is a complex concerning feelings and intuition-engine task, as it involves consideration, concerning feelings and intuition, semantic and fine motor abilities.

Among dysgraphia, kids or women have a harder time preparing and executing the literature of sentences, conversation, and even individual reports. It's not that you don't have the skill to state, spell, or recognize letters and conversation. Alternatively, your intelligence has questions dispose of dispute and writing. Dysgraphia may be very discouraging and arduous for the character. Concerned body would feel different from possible choices and this can influence their pride and have a negative effect on their professors. So, discovery of dysgraphia at inception can be honestly beneficial for the youngster and persons and the doctors. If analysis is likely at early stages, former improvement is attainable. So, this model is formed to discover dysgraphia and help teenagers suffering from this disorder.

## 1.2 CHARACTERISTICS OF DYSGRAPHIA

- Tightened fingers
- Unique wrist, frame, paper tilt
- Excessive mistakes
- Confusion of upper and lowercase messages
- Confusion of impressed, easy messages
- Improper postcard size and shapes
- Incomplete flowing notes
- Wrong usage of line and border
- Slow in imitating
- Lack of attention about analyses
- Inverted letters
- Uneven spacing
- Improper letter heights

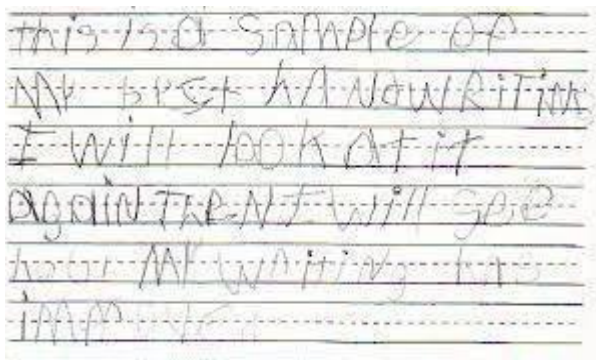


Figure 1: Handwriting of second-grade pupil suffering from dysgraphia

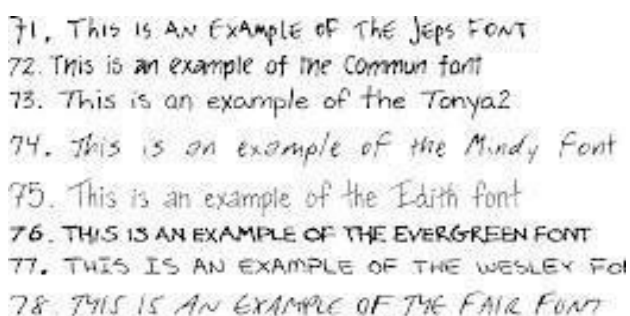


Figure 2: Student with good handwriting

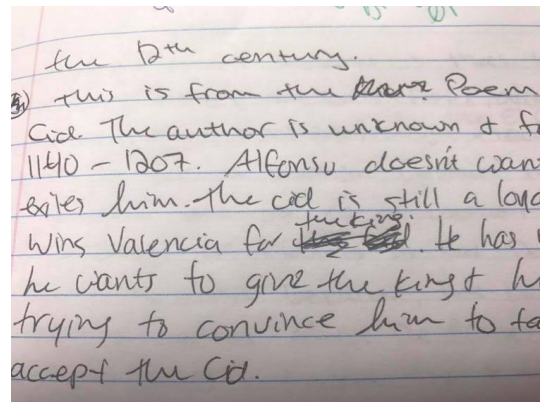


Figure 3: Student with bad handwriting

## 2. METHODOLOGY

### 2.1 DATASET AUGMENTATION METHOD

Data augmentation is a bunch of methods to falsely build how much information by creating new data of interest from existing information. This incorporates rolling out little improvements to information or utilizing profound learning models to create new data of interest.

Data augmentation is valuable to further develop execution and results of AI models by shaping new and various guides to prepare datasets. On the off chance that the dataset in an AI model is rich and adequate, the model performs better and all the more precisely. One of the means into an information model is cleaning information which is essential for high exactness models. Nonetheless, in the event that cleaning decreases the representability of information, the model can't give great expectations to certifiable data sources. Information increase methods empower AI models to be stronger by making varieties that the model might find in reality.

### 2.2 CNN

CNNs are used to distinguish designs in a picture. This is achieved by tangling over an idea and anticipated designs. The organization can find lines and corners in a dwarfed bunch front level of CNNs. We can then move these examples underneath and begin to perceive more perplexing characteristics as we adopt a more profound strategy. This trademark ensures that CNNs are exceptionally dynamic at recognizing objects in portrayals. The projected game plan utilizes CNNs to find dysgraphia composing from dysgraphia pictures portrayals.

The first layer is convolution layer. Pictures are convolved using channels or bits. Channels are small units that are applied across the data using a sliding window. It includes

taking component wise result of the channels in data and afterward add these particular properties for each sliding activity. The result of a convolution is that it has a 3-dimensional channel with variety and would be a 2d lattice.

The second layer is activation layer, it applies Rectified Linear Unit, in this layer, rectifier is applied to increment non-linearity in CNN.

The third layer is pooling layer, which includes inspection of elements. It is applied for each layer. It utilizes 2X2 max channel that has a step of 2. A channel would return maximum worth in highlights inside locale. Illustration of maximum pooling is when there are 26X26X32 volumes, presently utilizing maximum pool layer that has 2X2 channels and with on leg on each side, the volume is then decreased to 13X13X32 element map.

The fourth layer is the completely connected layer, it includes flattening. It changes the whole pooled highlight map lattice into solitary segment which is later taken care of by brain network for handling. With these completely associated layers, highlights are consolidated together to create a model. SoftMax or sigmoid is used to group the result.

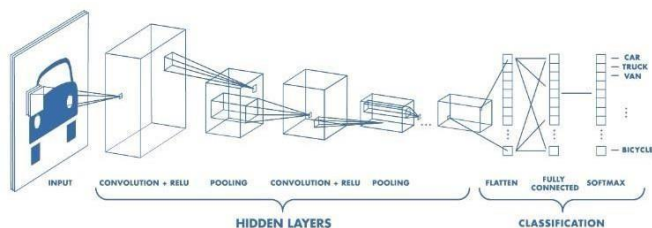


Fig 4: Architecture of a CNN Model

## 2.3. GRAPHICAL USER INTERFACE

We have built an application which will be available to everyone and the parents can check whether their children's handwriting is dysgraphia or not.

## 3. LITERATURE SURVEY

In accordance with the paper Labelling Developmental Dysgraphia Traits Applying Script Classification Designs (2017) [1], Dysgraphia is a commotion or trouble as a result of written language having connection with the mechanical details of the letter. The difficulties manifest as incompetent acting of longhand among youth the one argues least an average intellect level and the one destitute existed

identified as bearing some understandable neurological or concerning feelings and intuition-engine questions. The prevalence of scrawl troubles with elementary school scholars ranges from 10% to 34%. Dysgraphia can have deep associations for the individual in conditions of compromised self-figure and accomplishment in school. The aim concerning this study was to cultivate and test a mathematical model for changing between dysgraphia and able calligraphy to establish their performance traits. This study attracted labelling and typifying dysgraphia among Israelite literature teenagers. The SVM classifier shows accurate prophecies for 89 exhausted 99 calligraphy products, which leads to a veracity of 89.9%.

In accordance with the paper Dysgraphia detection through machine intelligence (2020) [2], a new script dataset was composed that consisted of various writing activities and a wide range of faces were extracted to get various facets of scrawl. Those were given to a machine intelligence treasure to envision if the manuscript was affected by dysgraphia. Before they distinguished several machine intelligence algorithms and erect high-quality results were achieved apiece adjusting pushing (Adaptive Boosting) algorithm. Finally, it proved that machine intelligence may be used to identify dysgraphia accompanying nearly eighty percent accuracy, while handling a heterogeneous set of matters. Cases with some harm or physical dislike to draft were expelled. Speed, jerk, acceleration, pressure, azimuth and peak were culled in form of heading of calligraphy sample. Classifier confirmation was conducted utilizing layered having ten of something cross validation, and all processes were recurring for ten periods. Categorization accuracy, feeling, and particularity over the ten duplications were averaged. Results showed it is likely to select youngsters with disorder with accuracy of 79.5% on a sample of kids of various ages using the AdaptiveBoosting and utilizing the RF and SVM algorithms. The accuracy score of the added models were high, 72.3% for RF classifier and 72.5% for SVM.

In accordance with paper, TestGraphia, a Spreadsheet Whole for the Early Diagnosis of Dysgraphia (2020) [3], this study plans an judgment agreement for BHK test by including writing face to a degree book size, impartial abandoned border, skewed lines, lacking scope 'tween words, sharp angles, defective links middle from two points reports, collision 'between two postcards, uneven height of letters, contradictory crest 'tween letters accompanying and outside enlargement, atypical messages, uncertain notes, traced memos, doubtful path. These facial characteristics should be deliberate by doctors and forms to pronounce dysgraphia. Certain countenance is approximately arithmetic-based, while additional physiognomy demands a doctor's interpretation and few visages may be automated.



In accordance with the paper, [4], it uses a reduced version of loop affecting animate nerve organs networks accompanying keras using tensor flow backend, a Scanning in of documents model was erected utilizing CNN. Accuracy of 86.14% is computed utilizing veracity principles of 85.12% and 87.18% from the data and the experiments. 5-Fold cross validation approach was second-hand. In every trial, the veracity profit was calculated every round and last veracity utilizing the mean principles of all rounds were calculated.

In another study, Towards Detecting Dyslexia in Babies' Handwriting Utilizing Affecting animate nerve organs Networks (2019) [5], an akin approach was second-hand using CNN in addition to keras and TensorFlow outside Scanning in of documents which managed to a veracity of 55.7%. So, scanning in of documents using CNN is favourable.

In accordance with the paper, Concept Classification utilizing SVM and CNN (2020) [6], SVM model that second-hand a very narrow dataset realized an accuracy of 93% and even though SVM is a very powerful method, achieving aforementioned an extreme veracity was still an anomaly. Utilizing dossier improving, the size of the dataset was in addition to increase and was acted on SVM repeatedly, it achieved a veracity of 82%. On favourably executing CNN, it achieved a veracity of 93.57% on the unchanging dataset. So, it decides that using CNN over an abundant improved dataset of countenances is better than using SVM because it determines larger veracity.

### 3. RESULT

Dysgraphia categorization in the period of being young helps to treat the offspring effectively and increases self-confidence of the offspring. Few existent plans involved in the dysgraphia categorization established machine intelligence methods and have the restraint of overfitting problems. The existent means have the restraints of lower effectiveness in categorization and non-discrimination discussion is not thought-out in the model. We achieved a total accuracy of 78.9% overall which can help in the detection of dysgraphia.

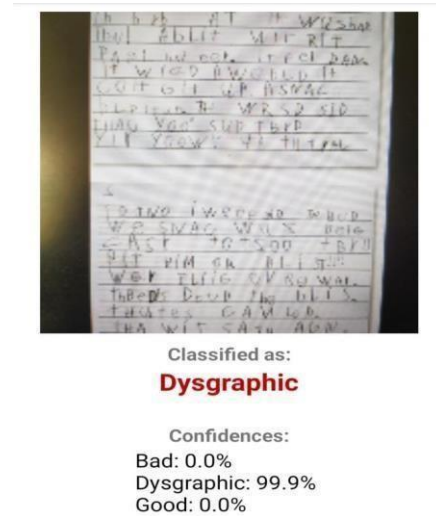


Fig 5: Dysgraphic image detection

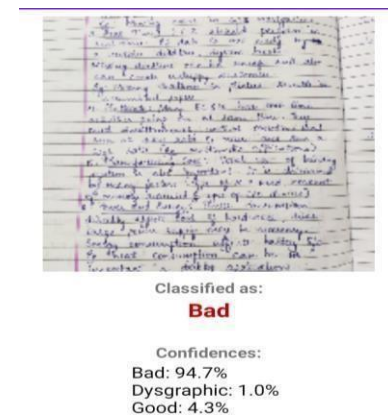


Fig 6: Bad Image detection



Fig 7: Good image detection

#### 4. CONCLUSIONS

Clearly dysgraphia is a hindrance for learning and improving in education. There is medication that help to destroy those obstacles using technology, guidance, and support. CNN architecture is put forward for bad, dysgraphic and good handwriting detection with an objective of high classification accuracy.

A genuine dataset was collected for the training and testing process which went smoothly. A training strategy comprised training model on the desirable patterns.

#### REFERENCES

- [1] Peter Drotar and Marek Dobes (2020) Dysgraphia detection through machine learning
- [2] Giovanni Dimauro(2020) TestGraphia, a Software System for the Early Diagnosis of Dysgraphia
- [3] Pratheepan Yogarajah, Braj Bhushan, (2020) Deep Learning Approach to Automated Detection of DyslexiaDysgraphia
- [4] Koteswara Rao Pandi, Ipseeta Nanda (2020), Image Classification using SVM and CNN
- [5] K. Spoon, D. Crandall and K. Siek. "Towards Detecting Dyslexia in Children's Handwriting Using Neural Networks." International Conference on Machine Learning AI for Social Good Workshop, 2019
- [6] Rosenblum, Sara; Dror, Gideon (2017). Identifying Developmental Dysgraphia Characteristics Utilizing Handwriting Classification Methods. IEEE Transactions on Human-Machine Systems, 47(2), 293–298[1]
- [7] G. Dimauro, V. Bevilacqua, L. Colizzi, and D. D. Pierro, "TestGraphia, a software system for the early diagnosis of dysgraphia", IEEE Access, Vol. 8, pp. 19564-19575, 2020.

[8]P. Drotár and M. Dobeš, "Dysgraphia detection through machine learning", Scientific reports, Vol. 10, No. 1, pp. 1-11, 2020.

[9] C. Taleb, L. L. Sulem, C. Mokbel, and M. Khachab, "Detection of Parkinson's disease from handwriting using deep learning: a comparative study", Evolutionary Intelligence, pp. 1-12, 2020.

[10] Fathima Ghouse, Kavitha Paranjothi, Revathi Vaithiyanathan, "Dysgraphia Classification based on the Non-Discrimination Regularization in Rotational Region Convolutional Neural Network" Vol.15, No.1, 2022.