



## Analysis Of Personality Based On Handwriting Using Deep Learning

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**Abstract:** Handwriting is one of the distinguishing characteristics that distinguishes a person's identity, and it is a method of identifying the writer's physical characteristics. It displays a person's genuine personality, including their actions, emotional outbursts, sense of self, rage, creativity, honesty, phobias, and a range of other traits. In this paper a multi-layered approach is proposed for analyzing personality traits by identifying the type of handwriting and classify the personality of the individual human being using deep learning models such as Resnet 34 and YOLO v5 model.

**Index Terms -** Handwriting Analysis, Personality Classification, Feature, Deep Learning.

### I. INTRODUCTION

Every person has unique features like fingerprint and handwriting. The handwriting reveals the psychological and physiological conditions of an individual person. A person's conduct, attributes, talents, characteristics, social connectivity, and knowledge may all be used to determine how unique they are, as these things all reflect their unique personality. Handwriting analysis to predict personality traits was done manually, and the accuracy of the analysis is dependent on the graphologist's skills. The graphologist is also prone to fatigue when several samples are to be analyzed [2]. This paper focuses on the handwriting analysis [1] process to detect the various personality traits of individuals [4] and classify them into different categories based on their handwritten documents. We propose a method for analysing real world handwritten text samples with CAD solution. The analysis is done for specific features of the sample for determining various characteristic behavioral traits of the person. We have considered various parameters of the handwritten sample like Margin, Baseline, T-bar and Slant to determine corresponding traits [3],[6]. The proposed solution will help individuals and graphologists to increase their speed and efficiency in the analysis process. Deep learning techniques like YOLO v5 and Resnet 34 will be implemented to improve the efficiency of the tool.

### II. MATERIALS AND METHODS

#### A. DATASET

In this paper, we have used custom dataset which contains 3000 images taken from Google Images and Handwritten samples.

**Table 1 : Distribution of Dataset images**

<i>Handwriting Type</i>	<i>Number of Images</i>		
	<i>Train</i>	<i>Test</i>	<i>Valid</i>
Ascending	100	100	100
Calligraphy	100	100	100
Cursive	100	100	100
Descending	100	100	100
Fancy	100	100	100

Italic	100	100	100
Letter space	100	100	100
Narrow space	100	100	100
Print handwriting	100	100	100
Slant handwriting	100	100	100
<b>Total</b>	<b>1000</b>	<b>1000</b>	<b>1000</b>

This dataset is used in identifying the handwriting types of a person which helps in classification such as Agreeableness, Conscientiousness, Influential Factor, Neuroticism and Openness personality traits [8].

## B. TRAINING AND VALIDATION OF MODELS

Deep learning models with a large set of labelled data and neural network topologies with multiple layers provide excellent accuracy and performance.

### a) Yolo

This statement is abbreviated as "You Only Look Once." Convolutional neural networks are used to recognise items instantaneously (CNN). To detect objects, the technique requires only one forward propagation through a neural network, as the name implies. In other words, a single algorithm is used to forecast the entire image.

### b) VGG16

Simonian et al. VGG16 is a 16-layer neural network with 138 million parameters, 13 convolutional layers, and three fully connected layers. The final two layers are max-pooling and SoftMax. A RGB image with a defined size of 224 by 224 serves as the conv1 layer's input. To increase the network's dimension, further 3 x 3 fully connected layers were added.

### c) VGG19

Simonyan et al. VGG19 was proposed. Because it includes 19 layers, it has a faster convergence and less overfitting. The only preprocessing step was to subtract the mean RGB value from each pixel value received throughout the whole training set. Max pooling is followed by a Rectified linear unit (ReLU), which increases nonlinearity, improves classification, and speeds up computing. The last softmax function is added after the third fully connected layer.

### d) Resnet

ResNet, which contains less parameters than the VGG network, was proposed by He et al. ResNet50 and ResNet152 V2 versions are used, with 50 and 152 layers, respectively, and where the shortcut link known as "skip connections" changes the design into a residual network. A batch normalisation layer is removed from the residual network using identity connections, along with a 3 x 3 convolution layer and a Relu Activation Function. The observed accuracies of several models are given and compared. The results are further investigated by generating a confusion matrix from training and test images. Using examples of the inference code's handwritten graphics, the time complexity was also determined. High levels of classification accuracy are made possible by deep learning, however it is unreliable and can forecast incorrect results for current source data.

## C. BEST MODEL SELECTION

The size, complexity, and runtime of the data set also determine how effectively deep learning systems classify Personality type .F1 scores, cross-validation scores, and kappa coefficient values are used to automatically pick the best model with good performance metrics and low run-time complexity. Applying reinforcement learning optimization techniques, the model's hyper-parameters are tuned on the dataset. The suggested strategy for choosing the best model involves less time and processing power.

## D. PERSONALITY ANALYSIS MODEL

The personality analysis models works in 3 steps. The first step is detecting the type of handwriting using object detection algorithm called YOLO v5. The second step is personality type classification based on the detected handwriting type using Resnet-34 algorithm. The final step is to provide the description of the personality of an individual person.

### a) YOLO v5

Convolutional neural networks are used to build a model that recognises things in real time. Using a single neural network, this method analyses the entire image, divides it into pieces, and forecasts bounding boxes and probabilities for each component.

These bounding boxes are weighed by the predicted probability. It then presents discovered items after non-max suppression, which ensures that the object identification algorithm only recognises each object once.

#### b) Reset 34

As name suggests, ResNet- 34 has 34 layers. It addresses the vanishing gradient problem with identity link connections that skip one or more layers. The ResNet backbone is portable to many applications, including image classification used here. This implementation of ResNet-34 is built using Fastai, a low-code deep learning framework. The following algorithm describes the steps to interpret the prediction output of deep learning.

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#### Algorithm : Handwriting Detection & Personality Analysis

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**Input:** Handwritten Image  $I_{(x,y)}$  from dataset.

**Output:** Detected Handwriting style  $I_{D(x,y)}$ , handwriting type  $hI_{D(x,y)}$  and Classified personality based on handwriting type  $J_{D(x,y)}$ , Personality type  $P_{D(x,y)}$

$h_D$  → Handwriting type

$Resnet()$  → Resnet-34

**Step 1:** Input the image  $I_{(x,y)}$  to handwriting detection model using Yolo v5 to detect the image.

**Step 2:** Check the image for type of handwriting style.

**Step 3:** Apply Resnet-34 for classified dataset to get personality type on detected handwriting type.

**Step 4:** Check the image for type of Personality based on handwriting type detected.

**Step 5:** Analyze the characteristics of Personality which is classified.

The below figure represents the working of Personality Analysis.

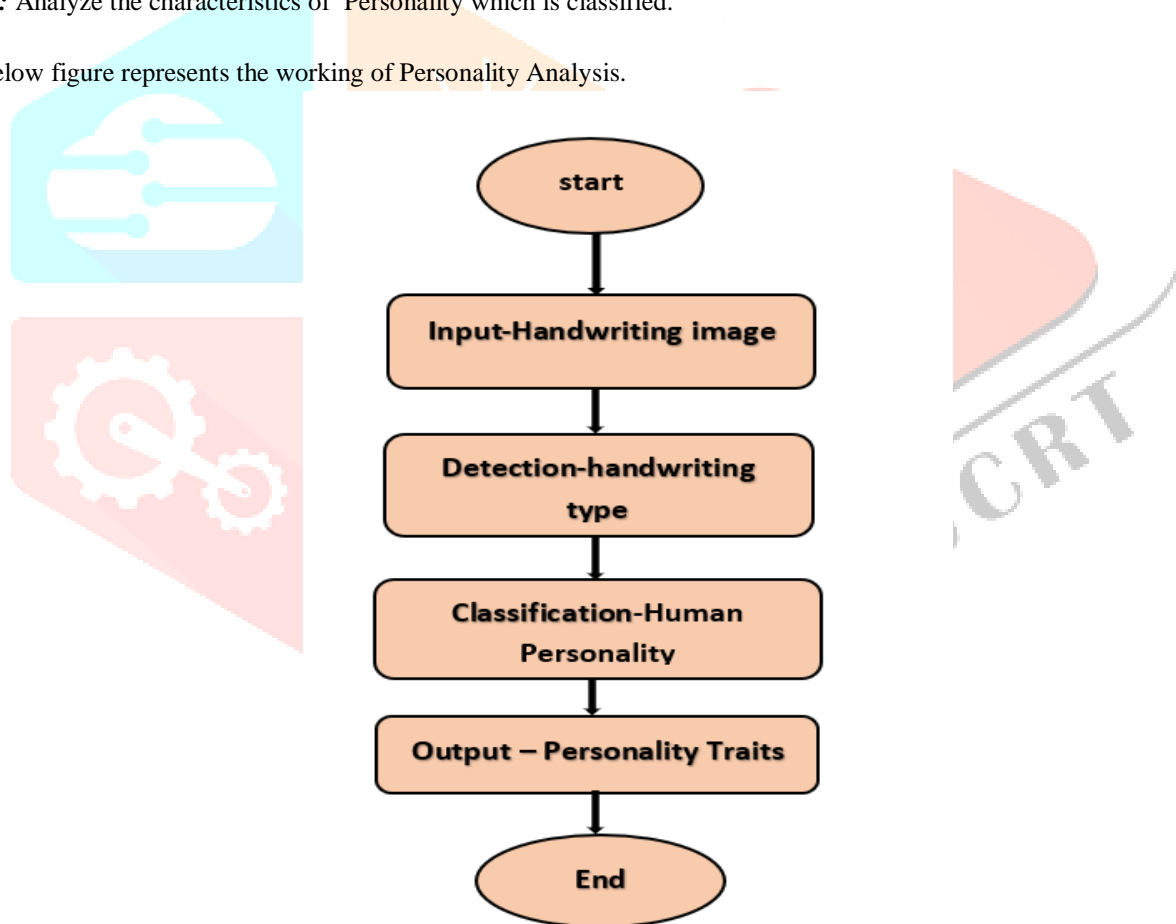


Fig.1. Personality Analysis System

The following image represents the correct result, with the predicted human personality based on handwriting style and the recommendations given confidently as a result of the system, lending confidence to the predicted result.

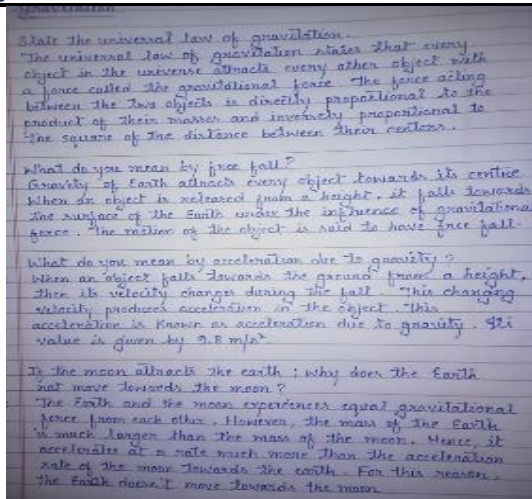
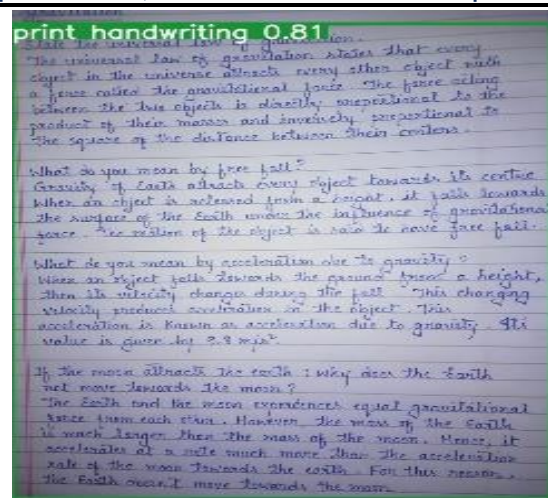


Fig.2. Input Image



Detected Image

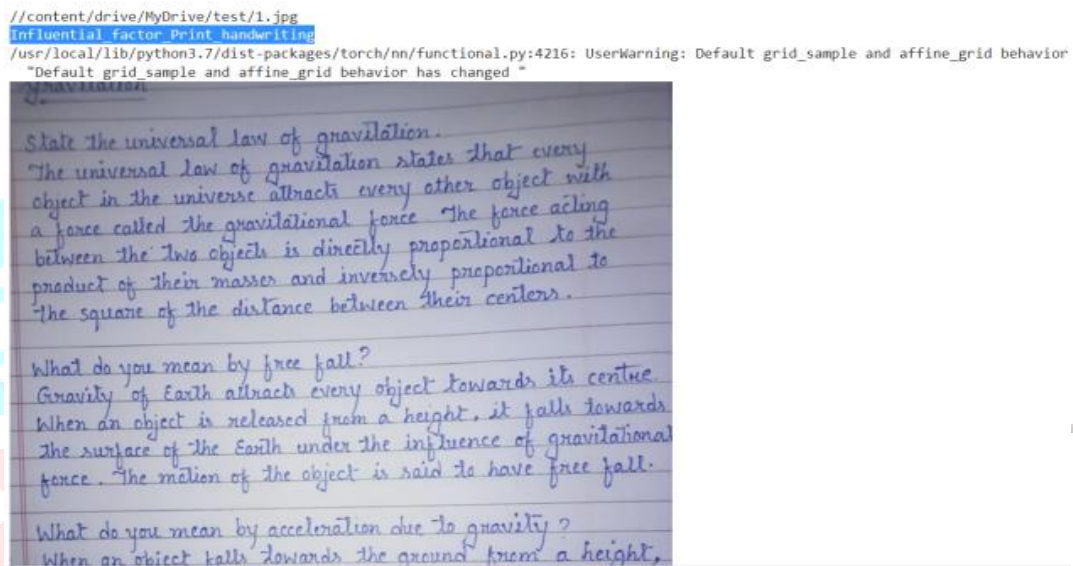


Fig.3. Classified Image

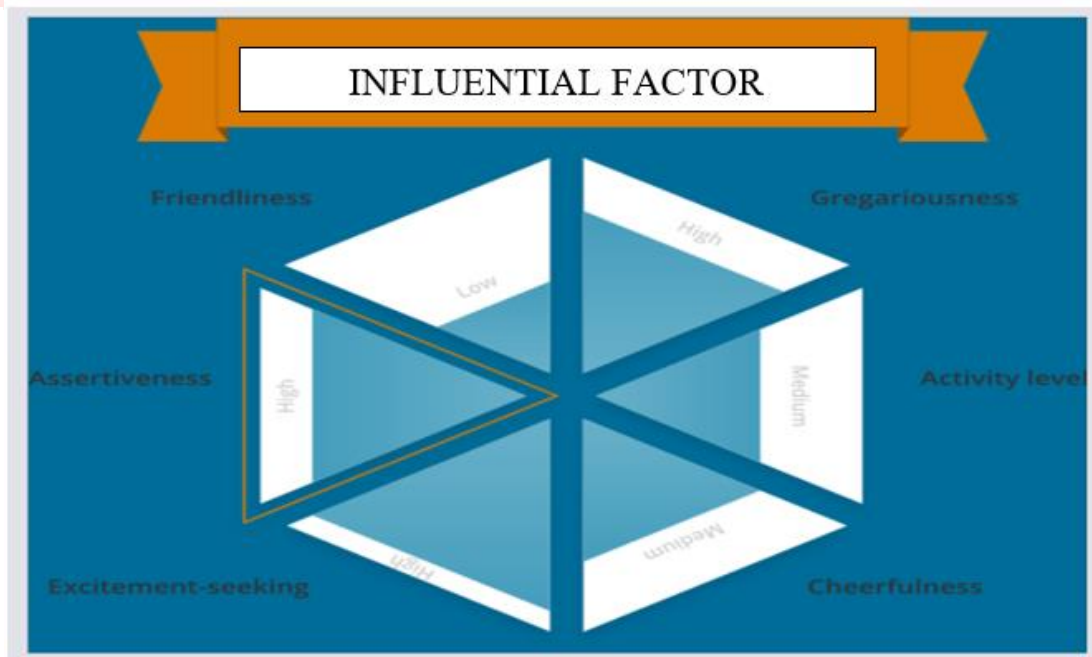


Fig.4. Personality traits

E. PERSONALITY TRAITS

We created a metadata-driven, content-based search that provides detailed descriptions of human personalities predicted by personality analysis models. Through extensive study and potential fixes, metadata is created to help end-user users better understand someone's personality.

## I. EXPERIMENTS

### A. EXPERIMENTAL EQUIPMENT

On Windows OS and NVIDIA Tesla K80 with 12 GB memory, all experimental investigations for developing deep learning models were assembled with GPU support. TensorFlow 2.4, Keras 2.3.4, and Python 3.7 were used to create the source code.

### B. TRAINING

By randomly dividing the entire data set, a training data set and a test data set are created. Utilizing the test set, the trained model was assessed. The quantity of pictures utilised for training, testing, and random testing is displayed in the following table. For the web, crowdsourced information and collected photographs are referred to as random test data. Techniques for transfer learning were used to create the CNN model. We enhanced the CNN model to categorise all of the dataset's categories using the pre-trained ImageNet dataset in order to speed up learning. To reduce training time and prevent overfitting, his ImageNet dataset employs pre-learned weights that were developed on 1.2 million photographs from 1000 classes. Due to the dataset's ten classes, the final fully connected layer (FC), which initially had 1000 classes, was reduced to ten. The layers of the pretrained model can now be trained separately. Using the categorical cross-entropy loss function, the final layer's softmax activation function was selected. An early stopping approach was employed with a perseverance of five during the training procedure. The various training parameters utilised to train the various model classes are displayed in Table 2.

**TABLE 2: Training Parameters**

<i>Model</i>	<i>Image Size</i>	<i>Epoch</i>	<i>Batch size</i>	<i>Lr</i>
Yolo v5	416 *416	500	16	0.1
Resnet 34	224*224	100	20	0.1

### C. PERFORMANCE METRICS

The handwriting dataset is divided into ten separate classes. In order to calculate the performance score for each deep learning model, clinical photos that were correctly categorised were classed as true positive (TP), while some true negative (TN) images were classified as wrong. False positive (FP) photos are those that have been wrongly classified, and false negative (FN) photos are those that have been correctly classified (FN).

The precision (PR), recall (RE), and F1 parameters used for a preliminary analysis of CNN model performance are given by equations 1, 2 & 3 [38].

Precision is defined as the ratio of True Positives to False Positives (True Positive plus False Positive). (1)

Recall = True Positive / (True Positive + True Negative) (2)

The F1 score is calculated as  $2 * \text{Precision} * \text{Recall} / (\text{Precision} + \text{Recall})$  (3)

## IV. RESULTS AND DISCUSSION

Finding cutting-edge deep learning models for categorising personality traits so they may be utilised for real-time prediction was the main objective of this study. Various deep learning models were trained using deep learning techniques. The average F1 results that were used to assess how well these models performed on the test data set are shown below.

### a) YOLO V5 accuracy

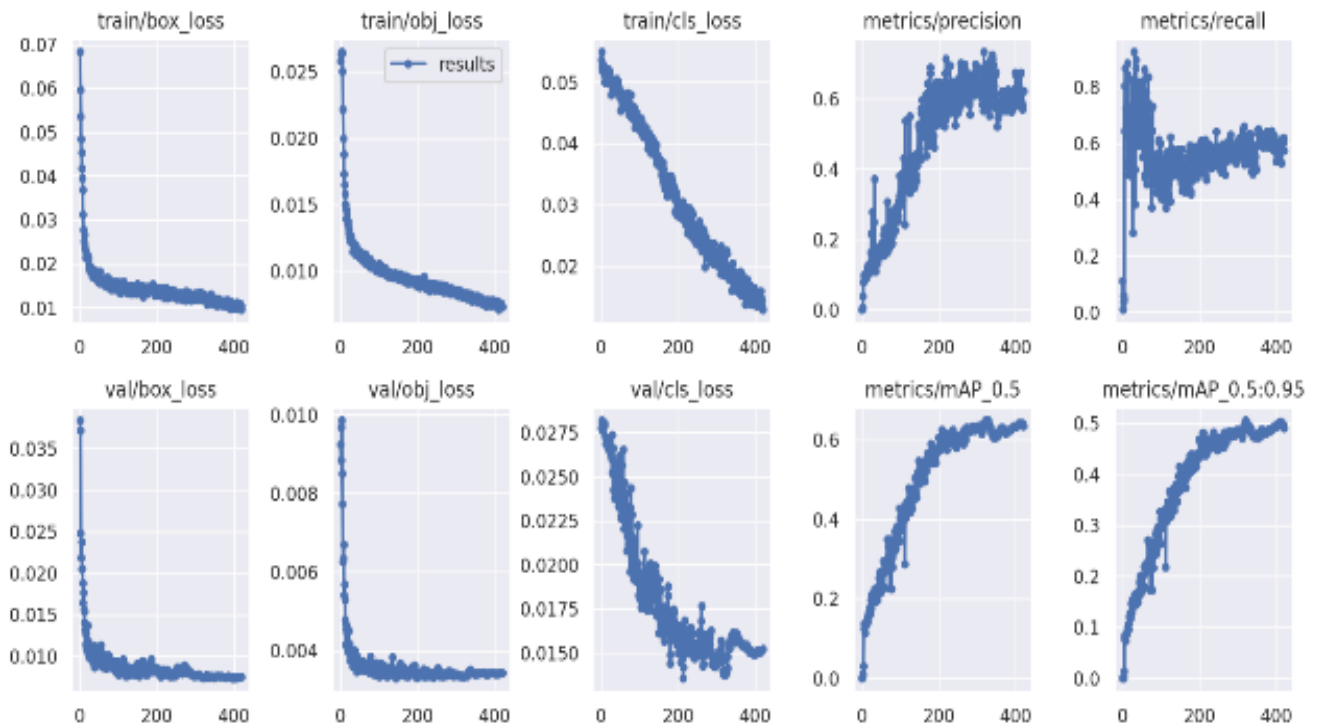


Fig. 5. Accuracy Metrics representation for Detection Model

a) **RESNET 34 accuracy**

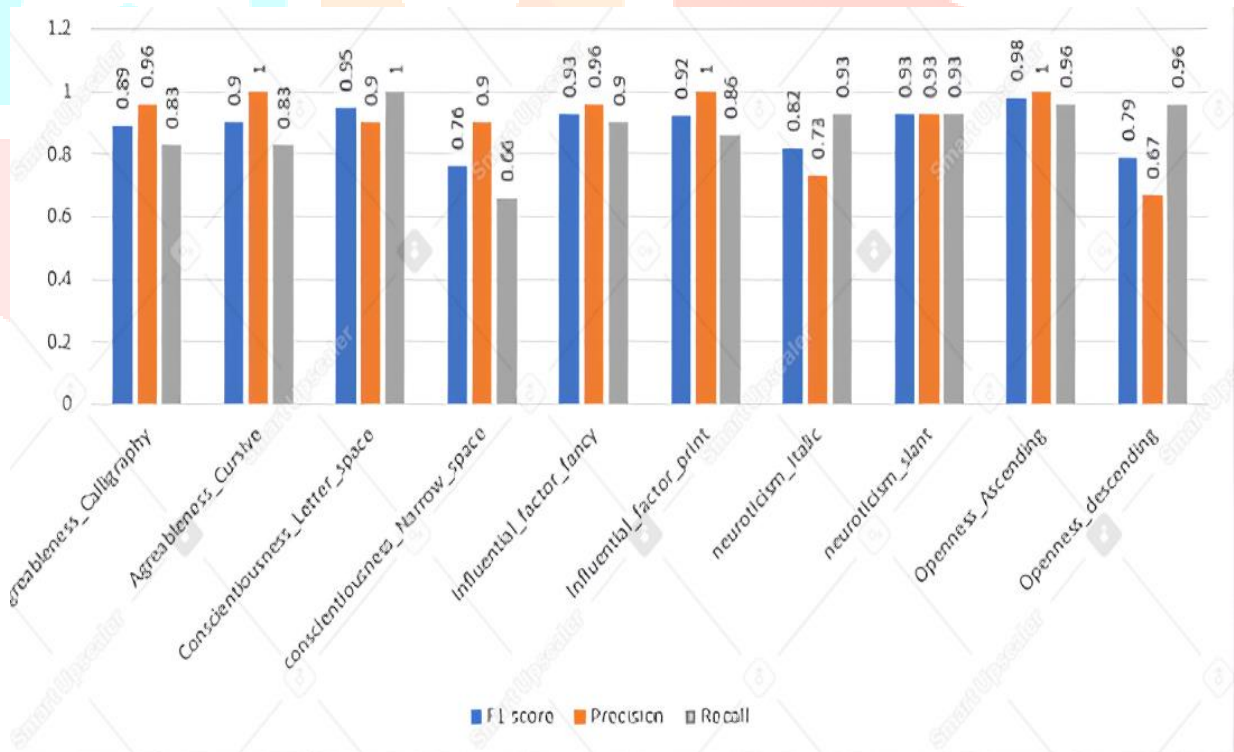
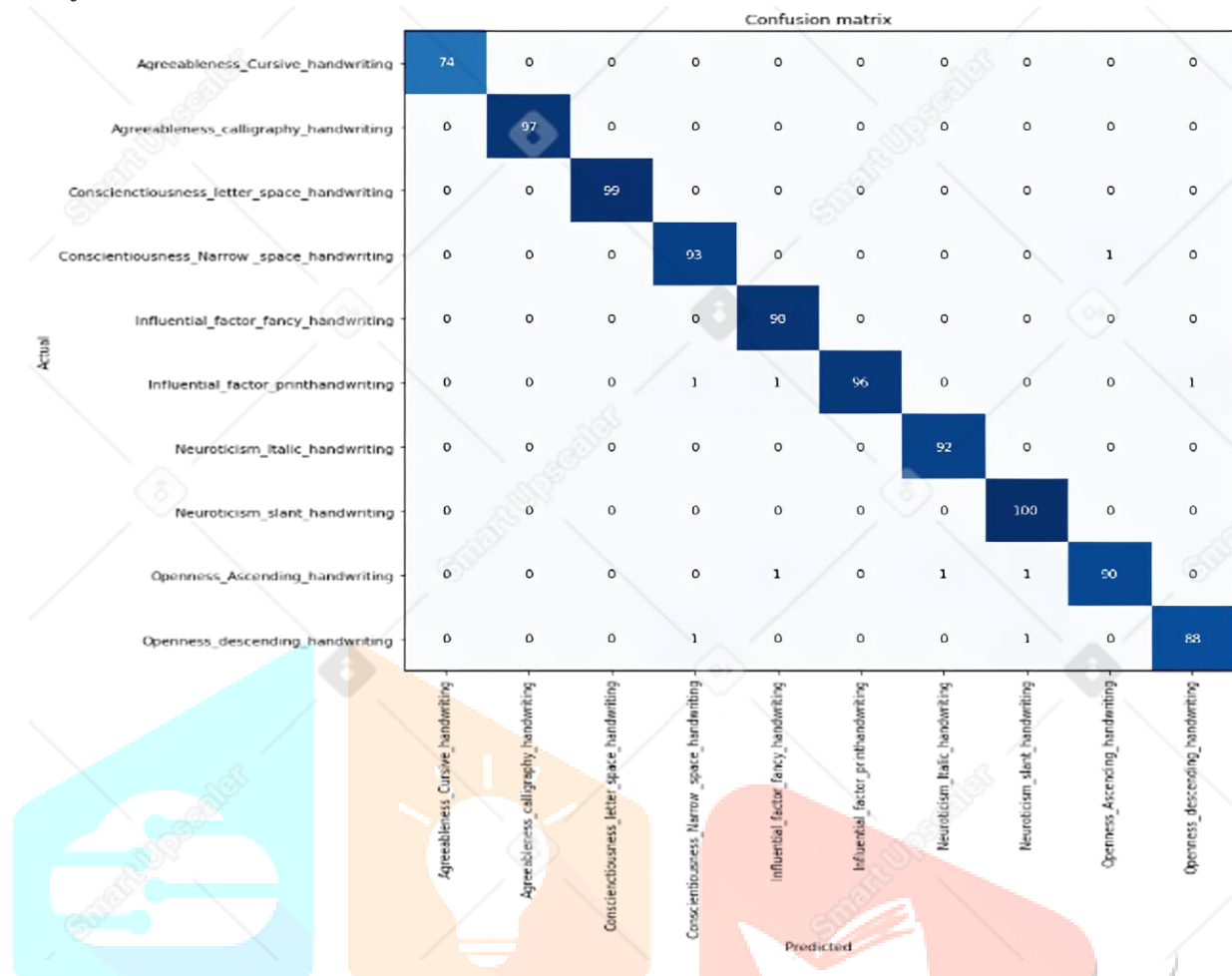


Fig.6.F1 score , Precision, recall metrics representation for Resnet 34 model

b) *Confusion Matrix*

**Fig.7. Accuracy metrics representation for classification model using Bar chart and Confusion matrix**

The average F1 for Yolo v5 was 0.95 and for Resnet 34 was found to be 0.91.

## V. CONCLUSION

Computer-aided diagnostic systems have recently become more popular because to deep learning approaches (CADs). Real-time handwriting type detection and personality classification provided insight into the classification in order to increase user help and trust in this research. This paper identifies the optimum deep learning classification architecture utilising multi-class handwriting data to infer a real-time application. Then, using metadata, provide a detailed explanation of the predicted personality. The YOLO v5 and Resnet 34 models were found to be the best architectures for detecting the type of handwriting and personality classification, with F1 scores of 0.95 and 0.91 on the handwriting dataset, respectively.

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