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An Enhanced Model for Detecting and Interpreting Examination Impersonators' Handwriting in Nigerian Universities using Convolutional Neural Networks

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ABSTRACT : *The problem of examination malpractices by students of Tertiary Institutions in Nigeria has continued to increase due to impersonators and lack of innovative strategies such as the ability to compare and interpret the impersonator's handwriting. However, there have been several existing models to detect and interpret the handwriting of examination impersonators, yet despite the achievement of these models, there are still certain anomalies that promotes examination malpractices in Tertiary Institutions. In this work, we developed an Enhanced Model for Detecting and Interpreting Examination Impersonators' Handwriting in Nigerian Universities using Convolutional Neural Network (CNN). The methodology used is System Development Lifecycle Methodology (SDLC) in his approach. We implemented with JAVA Programming Language and MySQL Relational Database Management System as backend. The results show that handwriting recognition using deep learning technique and Convolutional Neural Network is a very powerful tool for problem solving, especially in the area of curbing examination malpractices in Tertiary Institutions. Furthermore, the total performance point of 23.0 clearly shows that our improved system outperforms other existing systems. This work could be beneficial to the Management of Tertiary Institutions in Nigeria and to any other institutions that deal with examinations since it provides relevant information on strategies involved in tracking down the examination impersonators.*

KEYWORDS: *Model, Interpretation, Handwriting, Convolutional Neural Network, Affine Layer, Impersonation*

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I. INTRODUCTION

The problem of examination malpractice by students of Tertiary Institutions has continued to increase due to impersonation and lack of innovative strategies such as the ability to compare and interpret the impersonator's handwriting. However, there have been several existing models to detect and interpret the handwriting of exam impersonators, yet despite the achievement of these models, there are still certain anomalies that promotes examination malpractices in Tertiary Institutions. This study addresses the need to improve the best existing model through the addition of a Convolutional Neural Network that involves the process of finding the author of a specific handwriting through comparison to existing scanned handwriting files in a database of the known writers. Furthermore, the improvement of the existing model lies on the implementation of the Convolutional Neural Network in order to generate a feature vector for each writer, and is then compared with the pre-calculated feature vectors stored in the database.

For the generation of vectors; the Convolutional Neural Network is trained on a database with known writers and after training, the classification layer is cutoff and the output of the second last fully connected layer is used as a feature vector. A nearest classification is also used for the identification of the writer. According to [1], handwriting interpretation is the task of identifying an author of a hand-written document by comparing the writing with the ones stored in a database. The authors of the documents in the database have to be known in advance for identification. For writer retrieval the documents with the most similar handwriting are searched, generally these are the documents which are written by the same writer. For this task a feature vector is generated, which describes the handwriting of the reference document and the distance to the pre-calculated features vectors of all documents in the dataset is calculated. For retrieval the documents are sorted according to the distance and for identification the writer of the document with the highest similarity (resp. the smallest distance) is then assigned as author to the document. Writer identification can be used for tasks in forensics like for threat letters, where the writing has to be compared with older ones so that connections between different letters can be established.

Also for historical document analysis; writer identification can be used to trace the routes of medieval scribes along the different monasteries and scriptoria, or to identify the writer of books or pages where the author is not known. Since often a database of known writers is not available for such tasks, the main goal of this approach is to perform writer retrieval. Thus, only a nearest neighbor classification is carried out which allows for searching of documents which have a similar handwriting as a reference document.

1.1Aim and Objectives of the Study

The aim of this study is to enhance the best existing model for comparing and interpreting impersonators handwriting using Convolutional Neural Network. The specific objectives are to:

i) develop a model for detecting and interpreting impersonators' handwriting using Convolutional Neural Network (CNN).
ii) implement with JAVA Programming Language and MySQL Database as backend
iii) compare our results with other Existing System in Handwriting Interpretation

1.2Analysis of Convolutional Networks

A Convolutional Network is a class of deep neural network that is most commonly applied to analyzing visual imagery. It uses a variation of multilayer perceptrons designed to require minimal preprocessing. Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field. The description of the process as a convolution in neural networks is by convention. Mathematically it is a cross-correlation rather than a convolution (although cross-correlation is a related operation). This only has significance for the indices in the matrix, and thus which weights are placed at which index [2].

Convolutional networks may include local or global pooling layers which combine the outputs of neuron clusters at one layer into a single neuron in the next layer. For example, max pooling uses the maximum value from each of a cluster of neurons at the prior layer. Another example is average pooling, which uses the average value from each of a cluster of neurons at the prior layer [3].

Typically the sub-area is of a square shape (e.g., size five by five). The input area of a neuron is called its receptive field. So, in a fully connected layer, the receptive field is the entire previous layer. In a Convolutional layer, the receptive area is smaller than the entire previous layer. Each neuron in a neural network computes an output value by applying some function to the input values coming from the receptive field in the previous layer [4].

1.3 Identification of Handwriting through Convolutional Neural Network

According to [5], the current state-of-the-art methods for writing identification either analyze the characters itself by describing their characteristics and properties which are then integrated into a feature vector. Since a binarization and segmentation of the text is necessary, the methods are dependent on these preprocessing steps. To overcome these problems other approaches consider the handwriting as texture and thus use texture analysis methods for the generation of a feature vector. Recent approaches use local features for the task of writer identification which originate in the field of object recognition. Otsu [5] presented an approach that uses Convolutional Neural Networks for writer identification and retrieval. He defined Convolutional Neural Networks as feed-forward artificial neural networks and is used by currently top ranked methods for object recognition of digits and speech recognition.

They have been brought to the field of text recognition by Otsu and are also used for text recognition in natural scenes. To the best of knowledge, this is Otsu's first attempt to bring this method to the field of writer identification and writer retrieval. Convolutional Neural Networks consists of multiple layers which apply various combinations of convolutions and fully connected neural networks. Since a feature vector is needed for the tasks of identification and retrieval, the last layer of the Convolutional Neural Network, which basically does the labeling of the input data, is cut off and the output of the neurons of the second last fully connected layer are used as feature vector. This vector is then used for the distance measurement between two different document images to describe the similarity of the handwriting. A writer identification method which is based on features extracted from text lines or characters is proposed by [6].

II. RELATED WORKS

Ryosuke et al [6] developed the Writer Identification for offline Japanese handwritten character using Convolutional Neural Network. The work proposed some features from Convolutional neural network (CNN) for writer identification. They used datasets of Japanese handwritten character, which is made up of100 kinds of words from each 100 writers. They also evaluated two natures of handwritten words: the potential of writer identification for each word in Japanese and handwritten words contain the writer own unique identities. These natures cause a variation of classification.

Leandro [7] developed the Patch-based Convolutional Neural Network for the writer classification Problem in music score; he suggested that the writer identification problem has been largely studied in the field of image processing. Music score writer identification is a particular problem that requires the identification of a music score writer, which is a complex task for musicologists. In addressing the issue, he developed a deep learning approach-based Convolutional Neural Network.

Huang [8] proposed the theory of object recognition: computations and circuits in the feed forward path of the ventral stream in primate visual cortex. The work discusses the derivation and implementation of Convolutional neural networks followed by a few straightforward extensions. Convolutional neural networks involve many more connections than weights; the architecture itself realizes a form of regularization. In addition, a Convolutional network automatically provides some degree of translation invariance. This particular kind of neural network assumes that we wish to learn filters, in a data-driven fashion, as a means to extract features describing the inputs.

Maggie [9] published an article on large-scale learning with support vector machines and Convolutional Neural Network for generic object pattern recognition. She analyzed Text detection as an important preliminary step before text can be recognized in unconstrained image environments. She also presented an approach based on Convolutional neural networks to detect and localize horizontal text lines from raw color pixels. The network learns to extract and combine its own set of features through learning instead of using hand-crafted ones. Learning was also used in order to precisely localize the text lines by simply training the network to reject badly-cut text and without any use of tedious knowledge-based post-processing.

Miguel [10] proposed an interpretation of Convolutional Neural Network for speech Regression from Electrocorticography. In his work, he showed that Convolutional Neural Networks are useful to reconstruct speech from intracranial recordings of brain activity and propose an approach to interpret the trained CNNs. Furthermore, he related the ability of a Convolutional Neural Network to be powered by deep learning technique.

III. ANALYSIS OF THE EXISTING SYSTEM

The application of Graphology Interpretation System (GIS) to the investigation of examination malpractices that involve the perpetuators' handwriting has being paramount in most Tertiary Institutions. Graphology is a technique that allows us to become knowledgeable of ourselves and also explore those who surround us. Through the study of letters called Graphological analysis, it is possible to study patterns of writing that identify the psychological state of a person and to evaluate the characteristics of their personality. It is an economical method, fast and exact. It is applied as a complementary graphical projective technique of psychology in order to detect slight or profound conflicts and to contribute to diagnosis and follow up. It is also applicable to other areas such as medicine, psychiatry, law, criminology, education and personnel selection in companies.

Graphological analysis requires writings and tools as further illustrated in **figure 3.1**. A spontaneous text as large and complete as possible shall be required (a letter longer than a single page, dated and signed, directed to someone of trust). Present and previous writings of the suspect shall be required. In addition, white plain paper without lines or grids is also used by the system. The pen of the suspected perpetuator must be the one that he or she uses regularly. If the person does not have a preference, a normal tip point is offered.

In order to successfully carry out the analysis, the following parts of a letter have been identified:

i. Strokes are the path made by the writer in a single impulse
ii. Down strokes are the thick strokes going downwards, descending on letters.
iii. Up strokes are the thin strokes going upwards, forming letters.
iv. Ovals are the central or middle area of writing described as the "eyes" of letters a, g, o, q, d, etc.
v. Upper extensions are the full strokes of the superior area of letters b, d, f, h, j, l, ll and t up to the middle area; considered upper extensions of the vertical lines of letters n and m, capital and lowercase.
vi. Lower extensions: are the strokes going downwards going from the middle area up to the lower end of letters f, g, j, p, q, y and z.

All letters have an essential area and a secondary one. Graphology Basics: Essential strokes and Accessories strokes Graphology Basics: Essential strokes and Accessories strokes Essential stroke: It is the un-expendable part of the structure, the skeleton that grants identity to the letter without which it cannot be identified. Accessory or secondary part: Is the unnecessary added trait that is not essential to the form of the letter. It is the “decoration” or ornament that may not appear. Loops: Are “eyes” that are formed by the intersection of profiles and crests. Graphology Basics: In letters we also identify different areas of writing which includes five zones. A survey on text detection can be found in. One can notice that the main effort is focused in finding out a sophisticated set of edge or texture-based features for a robust discrimination between text and non-text patterns.

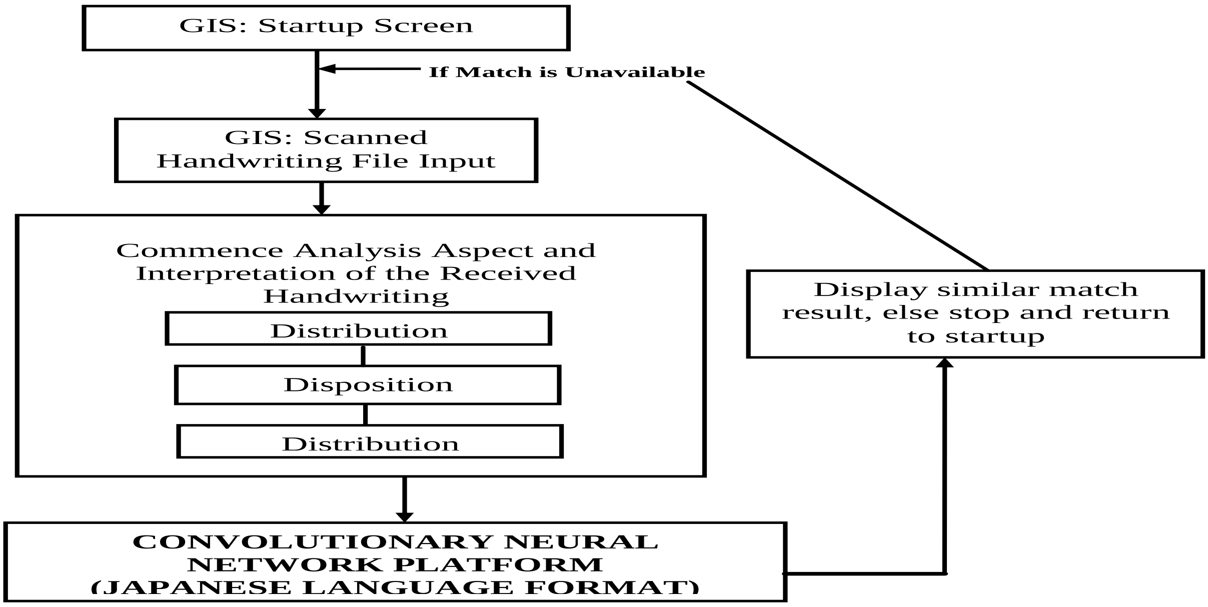


Fig. 3.1.Structure of Graphology Interpretation System (Existing System) (Source: [5])

3.1Analysis and interpretation aspects of the system

This component consists of three vital phases known as the distribution phase which distributes letters, words and lines for the analysis and interpretation in a specific order. The disposition phase involves the disposition of texts within the page taking into account the four margins, (page margins; sides of the page each have a meaning) that must be large enough cared for with a harmonic heading. Furthermore, the proportion phase is the equilibrium of the dimensions

• **GIS startup screen:**
The GIS startup screen welcomes a new user of the system, and further navigates the user to the other phases of the system.

• **GIS handwriting input platform:**
This platform of the system enables the user to browse and download an existing file that contains the handwriting to be interpreted by the system.

• **Input of second probable handwriting:**
Since the system was designed to compare and analyze multiple handwritings, it is mandatory to input another probable handwriting that might match the firstly inputted handwriting. This will enable the system to carry out in-depth analysis and matching process.

• **Interpretation details of the analyzed handwriting:**
This component further interprets the analyzed handwriting in terms of size, pattern and location source.

3.2 Disadvantages of the Existing System

The following disadvantage of the Existing System is:

i.Slow performance due to unavailability of a Convolutional Neural Network. This is because; the Convolutional Neural Network has inbuilt programmed neural perceptrons that connects to a centralized database management system which contains the students’ handwriting. In addition, the texts are in Japanese.

IV. ANALYSIS OF THE PROPOSED SYSTEM

This study intends to improve the Existing System of Handwriting Interpretation that utilizes the Graphology Interpretation System. Thus, this study proposes an Enhanced Graphology Interpretation System (EGIS). The improved system will include a Convolutional Neural Network that is made up of inbuilt programmed neural perceptrons that connects to a centralized database management system which contains the students' handwriting as illustrated in **figure 3.2**. Recall the role of a Convolutional Neural Network; which is a class of deep neural network that is most commonly applied to analyzing visual imagery. Convolutional Neural Networks uses a variation of multilayer perceptrons designed to require minimal preprocessing. This implies that the improved system will automatically analyze and interpret two handwriting inputs since it is linked to the centralized database management system which contains the students' handwriting. This concept alone will speed up the investigation process by the school management since comparisons and matches can be carried out effectively by the system.

Secondly, the Convolutional Neural Network's interface with the existing system will improve the traits of the handwriting analysis especially in terms of a specific handwriting size. This is because it is an objective parameter and can be measured. The relative features and their combinations are learned by examples via the back-propagation algorithm. In the next step of the scanning procedure, the responses collected at each scale are grouped according to their proximity in scale and space to form a list of candidate targets. The horizontal extension of a group is determined by the left and right extremes of the group, while the scale is averaged.

From the Proposed System, cases of multiline text are easily discarded in favor of the actual text lines that constitute it because the network is trained to reject multiline text. Finally, the rectangles of the candidates are inspected individually by forming local image pyramids around them and applying the network at each slice with step 1 in both directions in order to measure more effectively the density of the positive activations. The candidates that score low average activation are considered as false alarms and are rejected. Furthermore, in order to measure size we consider four or five ovals of the first two or three lines of text, four or five lines in the middle and four or five lines at the end of the writing. The same is done for upper extensions and lower extensions and an average is obtained. If size inequalities bigger than two mm are found, it is important to consign the same.

i) EGIS startup screen:

The GIS startup screen welcomes a new user of the system, and further navigates the user to the other phases of the system.

ii) EGIS handwriting input platform:

This platform of the system enables the user to browse and download an existing file that contains the handwriting to be interpreted by the system.

iii)Analysis and interpretation aspects of the system:

This component consists of three vital phases known as the distribution phase which distributes letters, words and lines for the analysis and interpretation in a specific order. The disposition phase involves the disposition of texts within the page taking into account the four margins, (page margins; sides of the page each have a meaning) that must be large enough cared for with a harmonic heading. Furthermore, the proportion phase is the equilibrium of the dimensions of letters between each other. It means there is equilibrium in sense of humor and judgment upon judging.

iv) Interpretation details of the analyzed handwriting:

This component further interprets the analyzed handwriting in terms of size, pattern and location source.

v) Convolutional neural network:

This is a class of deep neural network that is most commonly applied to analyzing visual imagery. Convolutional Neural Network (CNN) uses a variation of multilayer perceptrons designed to require minimal preprocessing. This implies that the improved system will automatically analyze, compare and match to any similar stored file in the CNN database. This concept alone will speed up the investigation process by the school management since comparisons and matches can be carried out effectively by the system, and also enable the curbing of examination malpractices.

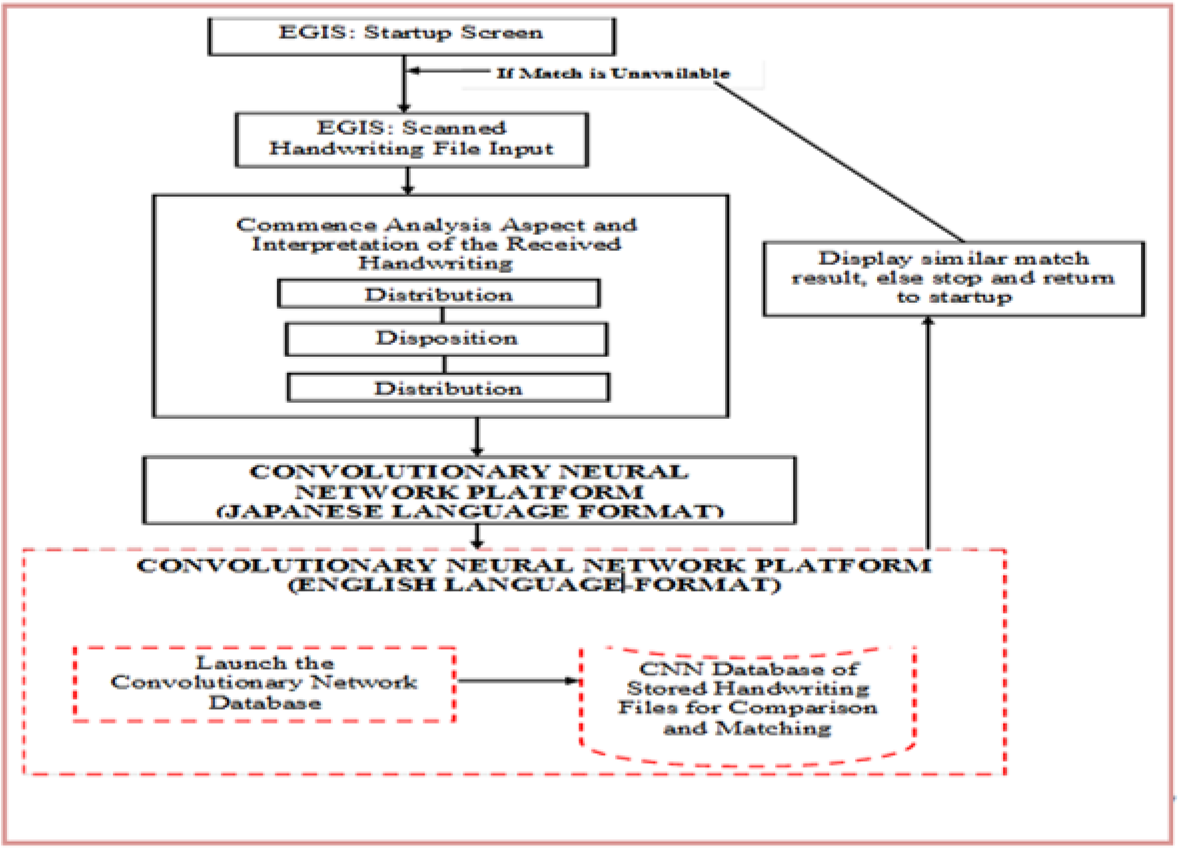


Fig. 3.2. Proposed System Architecture of an Enhanced Graphology Interpretation System

vi)Input of second probable handwriting:
Since the system was designed to compare and analyze multiple handwritings, it is mandatory to input anotherprobable handwriting that might match the firstly inputted handwriting. This will enable the system to carry out in-depth analysis and matching process.

4.1 Advantages of the Proposed System
The following advantages of the Proposed System are:

i) provision of in-depth knowledge for exploring students handwriting.

ii) economical, fast, reliable, flexible and easy setup methodology by management of Tertiary Institutions.

iii) complementation of graphical projective technique in order to detect slight or profound conflicts and to contribute to the diagnosis and follow up of examination malpractice cases.

iv) introduction of a Convolutional Neural Network that will improve its efficiency and performance through neural analysis, interpretation and interface to the existing database management system which contains the students' handwriting.

4.2 Existing System Algorithm

Step One: Start GIS (Graphology Interpretation System)
Step Two: Declare Variables K, HW, R UN AND PW. Where K represents the system startup variable, HW represents Handwriting, R represents Result, UN represents Username and PW represents password.
Step Three: Initiate K
Step Four: K = UN + PW (Optional)
Step Five: Input first HW
Step Six: Second HW
Step Seven: Compare and Analyze HW (first + second)
Step Eight: Output R

4.3Proposed (Modified) System Algorithm

Step One: Start IGIS

Step Two: Declare Variables K, HW, R, CNN, UN PW. Where K represents the system startup variable, HW represents Handwriting, R represents Result, CNN represents Convolutional Neural Network, UN represents Username and PW represents password.

Step Three: Initiate K

Step Four: K = UN + PW (Optional)

Step Five: Input HW

Step Six: Enable CNN

Step Seven: Analyze HW

Step Eight: Launch CNN Database

Step Nine: Scan CNN Database for matched HW

Step Ten: Prompt user if Match is found

Step Eleven: Display Match Result

Step Twelve: Stop

Step Thirteen: Quit System

V. RESULTS AND DISCUSSION

Figure 5.1illustrates the welcome screen of the Enhanced Graphology Interpretation System that is powered by Deep Learning Convolutional Neural Network (CNN). The welcome screen enables the user to understand the system in order to navigate to the next phase. Another importance of the expected result is that any text appearing in an image can provide useful information for the task of automatic image annotation and other related problems. In order to recognize this text, we first need to detect the real text area inside the image and separate it from the background. In simplified scenarios of uniform background, text detection is straightforward and can be accomplished with simple image thresholding or color clustering. In cases, however, of cluttered background and free environments, detecting text is a challenging task as the image background and the text itself as well are unpredictable. What is common in the above approaches is that text detection is considered as a two-phase process where, firstly, the engineer has to manually select an appropriate set of features and, in the second step, learning takes place.

The results also show that the introduction of learning in the first phase is a challenging task as image pixels result into high-dimensional input spaces, while the text pattern does not have any specific spatial distribution. We describe in this section how the trained Convolutional network is used to scan an entire input image in order to detect horizontal text lines of any height that may appear at any possible image location. In order to detect text at varying height, the input image is repeatedly sub-sampled by a factor of 1.2 to construct a pyramid of different scales. The network is applied to any slice (scale) of this pyramid individually. As the neural network uses Convolutional kernels at its first layers, instead of feeding the network at each possible image location, we can apply the network. The user then uploads the Scanned Handwriting File (SHF) of the suspected impersonator. Having done that, the user then uploads the SHF of the suspected impersonator by clicking on the browse button and selects the file from the situated memory location and finally submits. The submitted file will be displayed and viewed in the system's database. We also reported on a series of experiments with Convolutional neural networks (CNN) trained on top of pre-trained word vectors for sentence-level classification tasks. We show that a simple CNN with little hyper-parameter tuning and static vectors achieves excellent results on multiple benchmarks. Learning task-specific vectors through fine-tuning offers further gains in performance. We additionally propose a simple modification to the architecture to allow for the use of both task-specific and static vectors instance, instead of using an additional channel for the non-static portion, one could maintain a single channel but employ extra-dimensions that are allowed to be modified during training. Dropout proved to be such a good regularized that it was fine to use a larger than necessary network and simply let dropout regularize it.

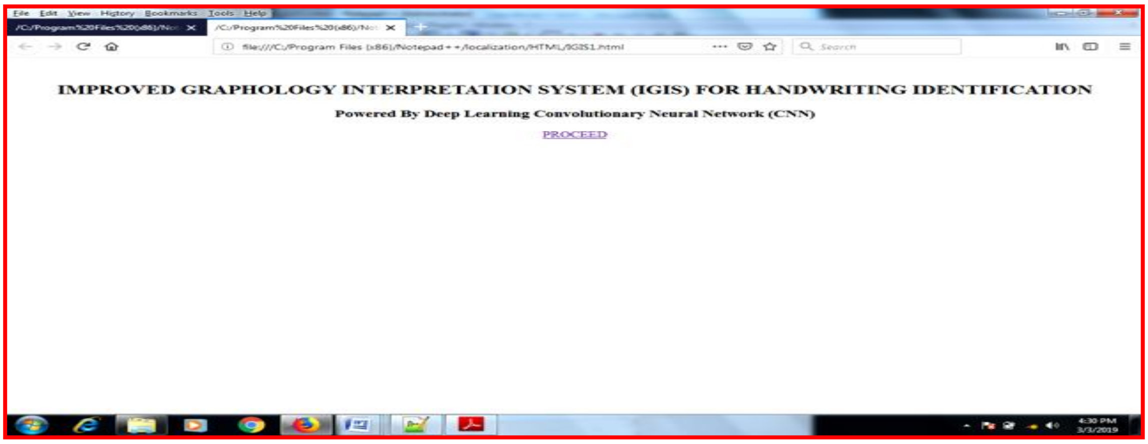


Fig. 5.1: IGIS: Welcome Screen

Fig. 5.2: IGIS: System Request Page

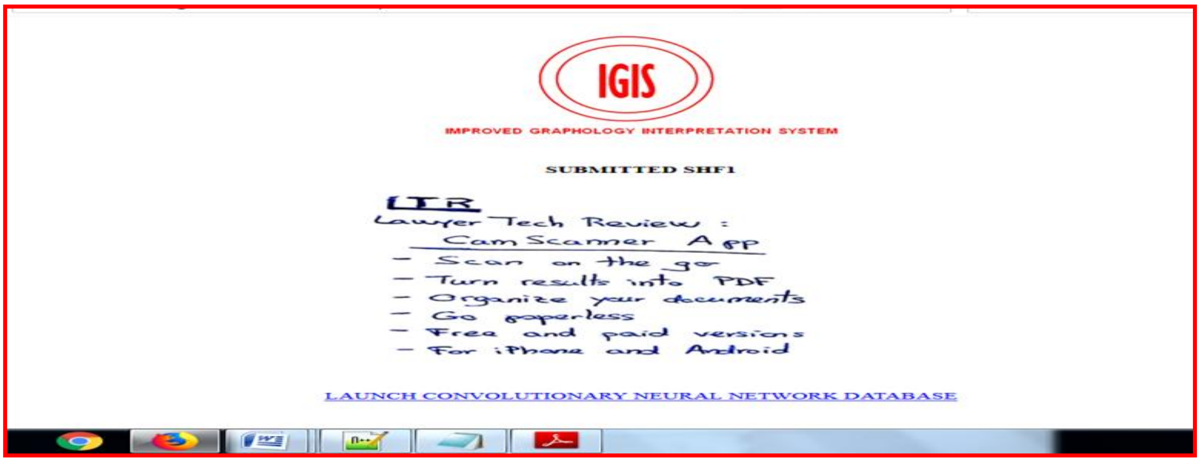


Figure 5.3: IGIS: Uploaded SHF

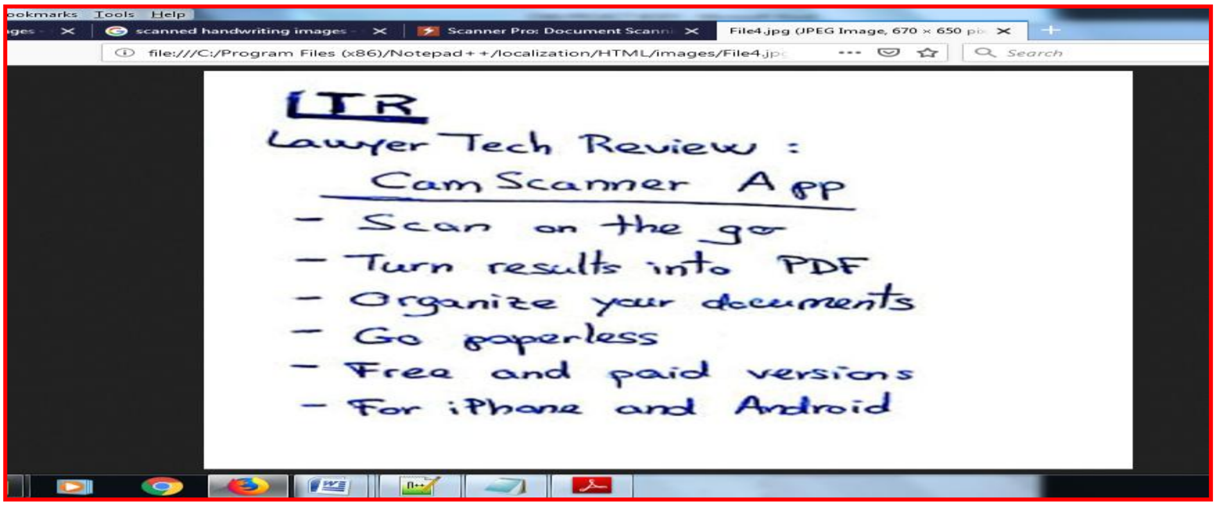


Fig. 5.4: IGIS: Uploaded SHF (contd.)

Fig. 5.5: IGIS: CNN Database

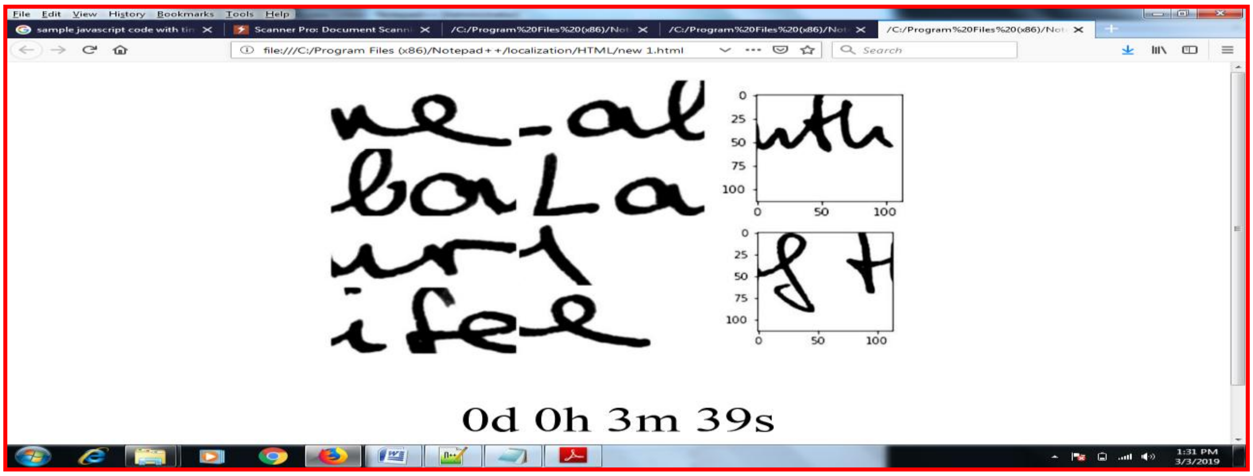


Fig. 5.6: IGIS: CNN Scan

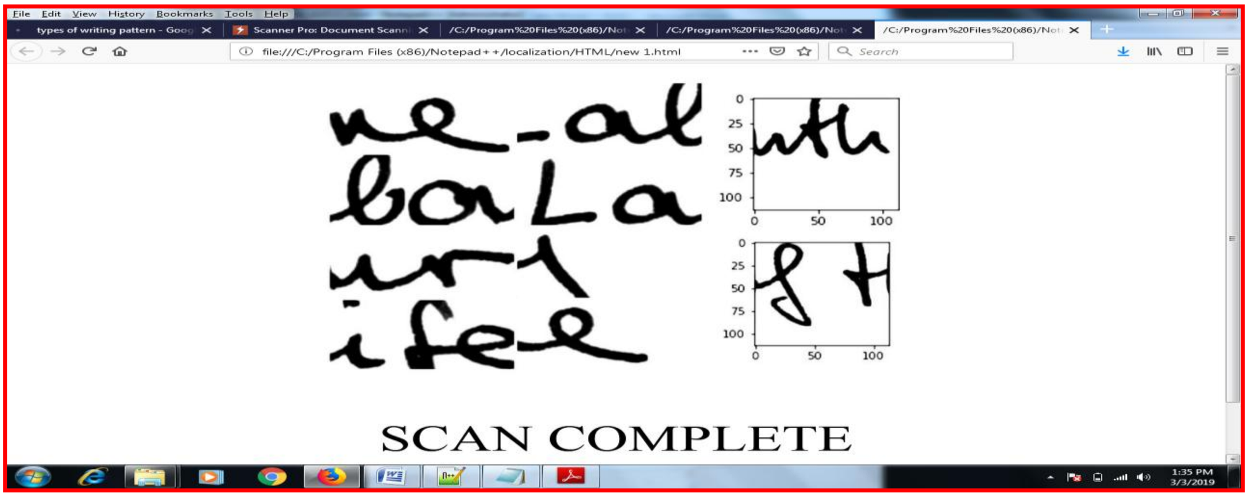


Fig. 5.7: IGIS: CNN Scan Completion

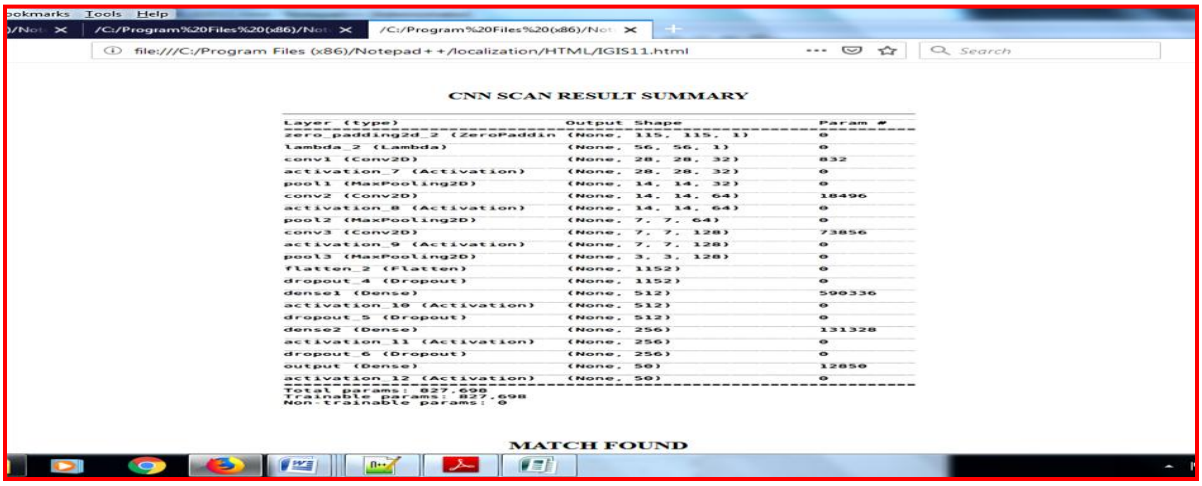


Fig. 5.8: IGIS: CNN Scan Result

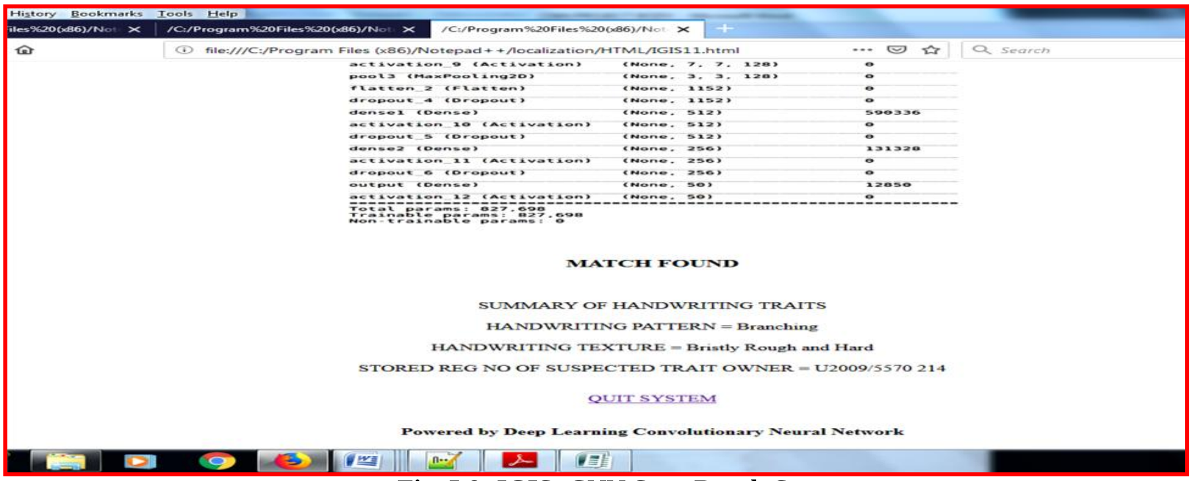


Fig. 5.9: IGIS: CNN Scan Result Summary

5.1 Algorithm / Program Performance Assessment

a) Assessment Variables

i) E = Excellent = 5.0

ii) G = Good = 4.0

iii) F = Fair = 3.0
iv) P = Poor = 2.0
v) VP = Very Poor = 1.0

Table 5.1: Ryosuke et al Algorithm on Writer Identification for offline Japanese handwritten character using Convolutional Neural Network (2018)

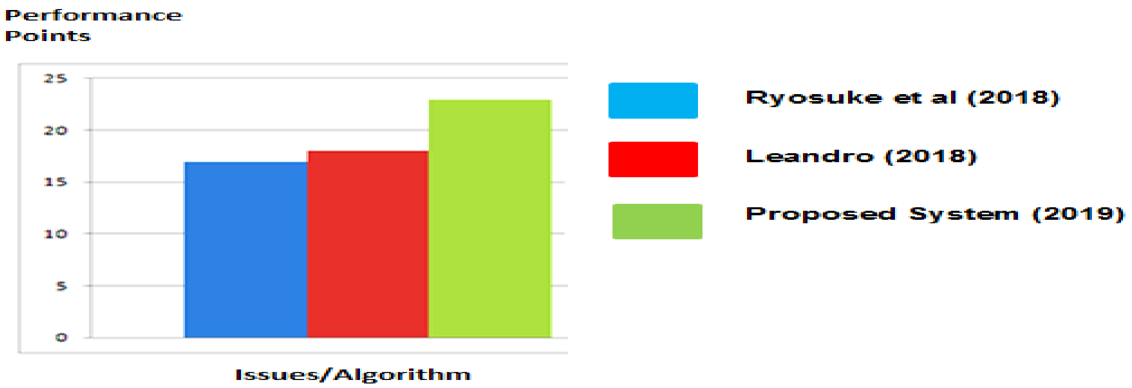
SN	PERFORMANCE AREA	VARIABLE	PERFORMANCE POINT
1	Datasets Used = OLE Objects	E	5.0
2	System's Database Storage Capacity = 10GB	F	3.0
3.	Processing Speed of the System = 10 Kilobytes per second	P	2.0
4.	Quick Response time of the system = 30 minutes	VP	1.0
5.	Open-Source Ability = None (Offline)	P	2.0
6.	GUI friendliness	G	4.0
TOTAL PERFORMANCE POINTS			**17.0**

Table 5.2: Leandro algorithm on Patch-based Convolutional Neural Network for the writer classification Problem in music score (2018);

SN	PERFORMANCE AREA	VARIABLE	PERFORMANCE POINT
1	Datasets Used = OLE Objects	E	5.0
2	System's Database Storage Capacity = 18.5GB	G	4.0
3.	Processing Speed of the System = 1.7 Kilobytes per second	VP	1.0
4.	Quick Response time of the system = 1hr minutes	VP	1.0
5.	Open-Source Ability = Enabled (Online)	G	4.0
6.	GUI friendliness	F	3.0
TOTAL PERFORMANCE POINT			**18.0**

Table 5.3: Proposed System algorithm on an Enhanced Model for Detecting Examination Impersonators' Handwriting in Nigerian Universities using Convolutional Neural Network (2019)

SN	PERFORMANCE AREA	VARIABLE	PERFORMANCE POINT
1	Datasets Used = OLE Objects	E	5.0
2	System's Database Storage Capacity = 40 GB (MySQL-Based)	G	4.0
3.	Processing Speed of the System = 100 Kilobytes per second	E	1.0
4.	Quick Response time of the system = 10 minutes	G	4.0
5.	Open-Source Ability = Enabled (Online)	G	4.0
6.	GUI friendliness	E	5.0
TOTAL PERFORMANCE POINT			**23.0**



VI. CONCLUSION AND FUTURE WORK

The war against examination malpractice in Tertiary Institutions is not yet won. Hence, we crave the indulgence of government to invest in more sophisticated systems that can also contribute to curbing the menace. As a result of that, we highly recommend this work to the management of Tertiary Institutions. Deep Learning Techniques through the application of Convolutional Neural Networks have continued to play an important role in problem solving. Handwriting recognition using deep learning technique is a very powerful technique for several reasons:

i) It automatically identifies deep powerful features
ii) Our approach of feeding in random patches makes the model text independent
iii) High prediction accuracy makes it possible to use this in practical applications

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