Doctor's Cursive Handwriting Recognition System Using Deep Learning

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Abstract—**Handwriting is a skill to express thoughts, ideas, and language. Over the years, medical doctors have been well-known for having illegible cursive handwritings and has been a generally accepted matter. The datasets used in this paper are samples of doctors cursive handwriting collected from several clinics and hospitals of Metro Manila, Quezon City and Taytay, Rizal. In this paper, we present the Handwriting Recognition System using Deep Convolutional Recurrent Neural Network that is developed in order to identify the text in the image of prescriptions written by the doctors and show the readable text conversion of the cursive handwriting. In this study two models were evaluated and based on the experimentation CRNN with model-based normalization scheme than the CRNN alone. This study achieved 76% training accuracy rate and the developed model was found successfully implemented in a mobile application, having achieved a validation accuracy of 72% for the validation set from the remaining 540 images of prescription. The mobile application was validated for the second time using the captured 48 handwriting samples written by the researchers and correctly identified 17 images out of 48 this gives us a 35% validation accuracy.**

Keywords—Doctors Cursive Handwriting, Optical character Recognition, Deep Convolutional Recurrent Neural Network, image processing, handwriting recognition

I. INTRODUCTION

Handwriting is a skill of man that is done to express thoughts, ideas and language. Doctors are well-known for having illegible cursive handwritings and it is a generally accepted matter. It is proven that even pharmacists who must administer the distribution of medicines prescribed for patients are also having difficulties on reading doctors' handwriting due to clinical notes that are illegibly written, and the content is unclear which resulted to many cases of medical errors [1]. A study from Texas, USA that is cited in [2] mentioned a real-life case where the cardiologist prescribed a 10 mg Plendil but the pharmacists misread it as 20 mg that causes severe consequences and eventually led to the death of the patient, pharmacists sometimes failed in reading prescriptions how much more for those non-medical people who are unfamiliar of medicines and the corresponding dosages needed. In a study from the Philippines, they collected preset prescriptions written by doctors. They assigned one set of assessors for each prescription that rated the legibility of the handwritings based on the results it concluded that the assessors are having difficulties in perusing the prescription which leads them in committing more errors [2].

The problem with recognizing human handwriting has influenced the development of present technologies [3]. The Handwriting recognition system is one of the advancements caused by human handwritings which have the capacity to detect characters in documents, images, touch-screen devices, and other sources that will be converted to machine-encoded form [4]. For the past years, different techniques and methods are utilized by researchers in reducing the gap between the human reading capabilities and the recognition systems [5].

Even there are many existing studies about handwriting recognition yet recognizing cursive characters is still a challenge due to deformations, inclination, size, different handwriting styles and incomplete strokes having a place with contiguous characters, ligatures, and noise. Since cursive alphabets are distinguished by stroke, one of the recognition errors encountered is when the stroke looks like the curves of some alphabets [6,7].

In this paper, the researchers aim to create a model that would be able to identify the words and numbers in the input image of Doctors Cursive Handwriting. This study will also help both the medical and non-medical people to lessen the difficulty of perusing illegible handwriting. The General objective of this study is to develop a Deep Convolutional Recurrent Neural System for text-line recognition of Doctors Cursive Handwriting.

II. REVIEW OF RELATED LITERATURE AND STUDIES

Every individual has their own specific style of writing thus, perusing penmanship is difficult at certain times [8]. Doctors are often standardized of having illegible handwriting [2]. Many studies and instances have proven that poor handwriting of doctors can lead to medical errors. An article from Reader's Digest has mentioned that the main reason why doctors have sloppy handwriting is that of the limited time they must talk with every patient causing them to rush when writing prescriptions. Another reason that made it more difficult to read doctors handwriting is due to some look alike medicine names and abbreviations that if written illegibly it becomes confusing for the readers [2,9,10].

Recognition systems are the ones responsible for categorizing input patterns to the corresponding entities. Entities differ from one system to another. The recognition systems that work with classifying of characters are called character recognition systems. Character recognition systems have one distinguishing feature which is the type of characters. There are systems for recognition of printed

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characters, typewritten characters or written characters [11]. A single character can be recognized easily but when it comes to dealing with cursive, and mixed cursive word, recognition could be difficult and challenging. Unique writing styles, shapes of alphabets and its sizes give complexity when it comes to recognizing the characters [12]. Character recognition is an essential area in image processing and pattern recognition fields. The fundamental point of character recognition is to make an interpretation of intelligible characters into machine processable configuration [13]. Through CR, the text in an image is converted into machine-readable text by using the format viz. ASCII or UNICODE [14].

Optical character recognition is software that used a more advanced usage of matrix method or also known as pattern matching. It is a procedure of interpretation of intelligible characters to machine readable characters in an optically scanned and digitized text [15]. Its features for recognition are enhanced and extracted from the stored bitmap image by utilizing digital image processing. The recognition of machine printed characters is likewise a part of optical character recognition [11]. Through OCR, the bitmaps of the template character will be compared with the bitmaps of the read character to determine which character they would closely match the most [16]. OCR is particularly useful and convenient when data that is understandable by individuals, and machines, is required, and some other data sources can't be assumed. Through script identification, the recognition of the text becomes easier by appropriately choosing the modalities of the optical character recognition system [17].

The neural network algorithm, neural network is a data modelling tool which can capture and represent complex input/output relationships. Neural Network Technology is inspired by the goal of developing an artificial system which could perform intelligent tasks that a human brain can do [18]. The primary step in character recognition is preprocessing and which is also known as an important phase to achieve a higher recognition rate [19,20]. In any OCR framework preprocessing is required because it enhances the image and diminishes the noise and misinterpretation of the letters [21]. In the off-line recognition system, the neural networks have risen as the quick and dependable tools for classification towards accomplishing high efficiency [20].

Recurrent Neural Network (RNNs) is a class of Artificial Neural Network utilized to produce sequences in different domains such as music, text and motion capture information. RNNs can be trained for sequence generation through taking steps one at a time and predict what comes next [22]. Unlike the typical recognizers that uses HMM, RNN systems does not have limitations when it comes to handling long term dependencies. Through recurrent connections, it can accumulate representations of previous input events in form of activations permitting them to model complex structures and it can have multiple layers which made them very effective in sequence modeling [30].

The Long Short-Term Memory is an RNN architecture intended to be better at storing and retrieving information than standard RNNs. LSTM has given advanced results in many sequences processing tasks, including speech and handwriting recognition [22]. LSTM architecture is different from the former neural network architectures and seems to overcome many problems from earlier architectures. The recurrent neural networks are known to be good at context ware processing and recognizing patterns occurring in timeseries but in traditional RNNs they are not presenting a competitive performance in large scale tasks like OCR. This problem is the reason why LSTM is designed, it is a non-linear recurrent network which have multiple 'gates' and additional feedback [23].

Deep Learning computers can learn from experiences and through hierarchy of concepts it can comprehend the world. Since computers can acquire knowledge from experiences, there is no need to have a human computer operator to specify all the knowledge that the computer needs. Through hierarchy of concepts, computers will be able to learn complicated concepts by building them out of less difficult ones [24]. In numerous software disciplines such as computer vision, speech recognition, language processing, robotics, bioinformatics, video games, search engines, online advertising, and finance it is proven that deep learning is useful in said areas [24]. Deep Learning made an advancement in a few research fields such as artificial intelligence, pattern recognition, computer vision and natural language processing [25].

Building a program that can provide better accuracy for handwritten characters [26] is not a simple task because even humans can commit errors in recognizing characters it varies depending on the writer [27]. There are already various existing handwriting recognition systems that have already used different algorithms such as K-means and Hidden Markov Model many quite succeed but in terms of recognizing cursive handwriting it is still a challenge. The deformations and loops made it difficult to recognize cursive characters. Most of the existing Handwriting recognition systems are only intended for non-cursive characters and numbers. As of now, studies that tried to create Cursive handwriting recognition systems obtained only 90% as a maximum accuracy rate.

III. Design and Methodology

The study implements the following approach that has four (4) stages as shown in Fig. 1 namely Data Collection, Pre-processing, Training of Data and Model Evaluation and Analysis.

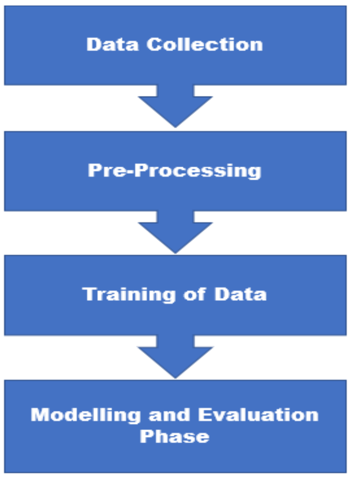

Fig. 1 . Phases of Methodology

A. Data Collection

The researchers requested doctors to write a preset prescription three times which contains twelve (22) medicine names with their corresponding instructions of use, this list is originally from the study [2] the researchers used this list of medicines and instructions of use because they consist of commonly prescribed and misread medicines and instructions based from the various studies that is also mentioned in [2] . The respondents used a Uni pin Fine Line 0.5 drawing pen and paper with bounded boxes with a size of 3x10 inches where each of the medicine names and instructions of use are written in it. The target participants will be at least fifty (50) doctors, initially, the researchers collected written prescriptions from 50 doctors. The collected written prescriptions were captured using a 13-megapixel phone camera. So, in total, our dataset consists of 1,800 images from several hospitals and clinics in Metro Manila, Quezon City and Rizal. The dimension (W x H) of the images used range from 1600 x 155 to 2793 x 1037. The researchers renamed each image using this format:

Number of try_Initials of the Doctor_Medicine name in the prescription

The name of the image file started in a number which could be 1, 2 and 3. These number represented the amount of trials made by the doctor. Since doctors were asked to write each prescription three times, number 1 was used for the image of sample handwritings written for the first try while 2 and 3 were used for the second and third try. The number was followed by an underscore (_) after that, the surname of the doctor was included in naming the file and for those doctors that had the same surname, the initial of their first name was added in the name of the file. Another underscore followed the surname of the doctor, the medicine name in the prescription written was the last one included in naming the image file, the sample of file names used for the images is displayed in Fig. 2 while in Table 1 shows the list of prescription used in this study.

1_Amagancia_Azathioprine.jpg 1_Amagancia_Ceftriaxone.jpg 1_Amagancia_Chlorpromazine.jpg 1_Amagancia_Dobutamine.jpg 1_Amagancia_Hydroxyzine.jpg

Fig. 2 Sample file names of the captured images

TABLE I. LIST OF MEDICINE NAMES WITH INSTRUCTION OF USE IN THE PRESET PRESCRIPTION

Prescription	Medicine
Prescription 1	Azathioprine: 3-5 mg/kg Per os OD
Prescription 2	Ceftriaxone: 2 g IV q24h
Prescription 3	Chlorpromazine: 10-25 mg Per os three times a day
Prescription 4	Dobutamine: 2.5-15 mcg/kg/min
Prescription 5	Hydroxyzine: 50-100 mg by IJ qds
Prescription 6	Lorazepam: 1 mg Per os 2 times a day
Prescription 7	Metronidazole: 7.5 mg/kg Per os q6hr
Prescription 8	Prednisolone: 5-60 mg per day qds
Prescription 9	Quinine: 648 mg Per os every 8 hours for 7 days
Prescription 10	Risperidone: 2 mg orally i/d
Prescription 11	Rituximab: 375 mg/m2 IV once weekly
Prescription 12	Tramadol: 50-100 mg as needed every 4 to 6 hours

B. Preprocessing and Cursive Handwriting Samples

After gathering sample handwriting data, the researchers took an image of each prescription and it is first submitted to cleaning before training and testing. This study used Zhang Suen thinning algorithm for pre-processing to thin the letters, symbols, and numbers inside the image or simply thinning the binary image. In Fig. 2 to Fig. 4 shown the original image, binary image and skeletonized image

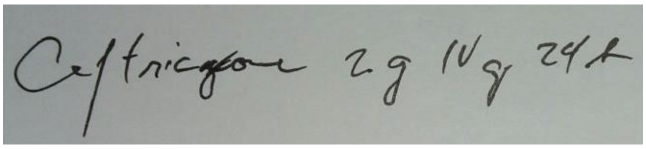

Fig. 2. Original Image

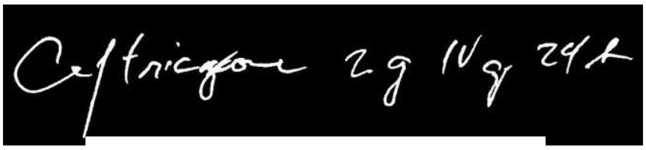

Fig. 3. Binary Image

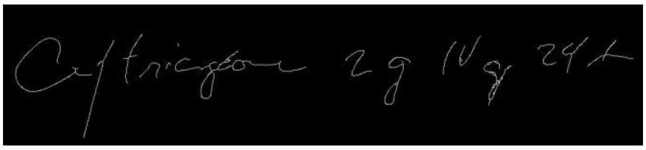

Fig. 4. Skeletonized Image

The skeletonized images were the ones used to feed in the training process. There is a square-shaped sliding window used to scan the text-line image and the movement of sliding window is the direction of the writing. The height of the window depends on the size of the image and its pixel is normalized to 64 pixels. To address the change of convolution filters, there is a window overlap of 2 pixels. The researchers used int64 data type for the sequence length. The sequence capacity adjusts depending on the length of the image.

After all the images were skeletonized each image will be subjected for labelling. The characters inside the image were identified. The researchers run a program in Python Spyder to automatically convert the input characters to ASCII. When the labels were successfully converted from string to ASCII, the researchers used a notepad to paste or edit the labels, it is important to take note that the Sorted list of classes or characters should start with <SPACE> that is 32 in ASCII conversion and subsequently it will now be converted to a thru a file. There is also the list file where the filename for each of the training image were shown.

C. Data Training

The preprocessed data were trained using a combined deep learning algorithm: Deep Convolutional Neural Network and Recurrent Neural Network.

The 70% of the dataset (equivalent of 1,260 images) were used for the training. The researchers used Open CV Python and Tensorflow for training.

After the preceding steps, the researchers proceeded to the training. The epoch size is set to 50 and the threshold is set to 10. Since, the researchers observed the training is not improving after the 35th epoch, early stopping is done. The researchers run the testing.py to display the decoded text file.

1) Deep Convolutional Recurrent Neural Network (CRNN)

Convolutional Neural Network is an algorithm that less requiring preprocessing unlike other classification algorithms. It takes an input image and identifies the important aspects and objects in it. This can apply relevant filters to capture the Spatial and Temporal Dependencies in an image. Also, it can reduce the included parameters and reusability of weights and achieve better fitting to the image dataset where their network is trained to understand complex images better [28]. While the Long Short-Term Memory architecture of Recurrent Neural Network can access long-range context and based on a study LSTM hold better results in handwriting recognition [29]. We also used the Rectified Linear Unit (ReLU) activation function because a study showed that it works better than sigmoid and tach activation functions. Based on a study that it has the advantage of being unaffected to the disappearing of gradient problem while being simple in terms of computation [25].

The researchers utilized a stack of 13 convolutional layers that has 3 x 3 filters and 1 x 1 stride. The convolutional layers are followed by three Bidirectional LSTM layers with 256 units that has one cell for each unit of LSTM, and after that, the max pooling is employed. The Rectified Linear Unit Activation function was also utilized since it introduces non-linearity [25]. The researchers used feature vectors extracted from the feature maps produced by the last convolutional layer, in each analysis window that has 64 x 64 pixels size, there are 16 feature vectors extracted and after all those steps the image will now proceed to the observation sequence. For each of the last 512 feature map's 16 columns, the 2-pixel height columns are concatenated into a 1024 (512 x 2) feature vector.

2) Connectionist Temporal Classification

The researchers used Connectionist and Temporal Classification because its system is end-to-end trainable. The convolutional filters and the LSTM unit weights are together learned within the back-propagation procedure. At the end of the BLSTM, we combined the forward and backward outputs. To speed up the training process, batch normalization was added after each convolutional layer. Together with the Connectionist Temporal Classification loss function, the network was trained in an end-to-end way. In the training of the network Adam Optimizer was used with initial learning rate of 0.001. After each convolutional layer batch normalization was added to accelerate the training in order to simply normalize each batch by both mean and variance. The network is also trained with CTC loss function. For the decoding both token-passing algorithm and beam search

IV. Results and Discussion

The researchers evaluated the prototype using the Accuracy percentage and F1 Score.

$$\textbf{\textit{Accuracy}} \frac{(\mathrm{TP+TN})}{(\mathrm{TP + TN + FP + FN})} \quad (1)$$

$$\textbf{\textit{F1 Score}} 2 \frac{(Recall*Precision)}{\mathrm{Recall + Precision}} \quad (2)$$

The researchers used 10 Batch Size and set the Train Threshold to 10 which will stop the training if the validation is not improving for ten consecutive times. Since the Training and Validation are already not improving after the 35th epoch, the researchers made an early stopping.

The researchers compared the performance of two model which is the plain CRNN and CRNN with model-based normalization scheme by computing their accuracy, F1-score and Aggregated Accuracy. The researchers run a program in Jupyter Notebook to get the aggregated accuracy and evaluation metrics of the two different models. The results are displayed in Table 2.

TABLE II. AGGREGATED ACCURACY AND EVALUATION METRICS OF TWO MODELS

Model	Accuracy	F1	Precision	Recall
CRNN	73	82	79	85
CRNN + model-based normalization scheme	76	84	80	89

As reflected in Table 2, the CRNN with model-based normalization scheme performs better than the plain CRNN since the notion of the variability in the writing scale to the test data is introduced. Since the CRNN with model-based normalization achieved a 76% accuracy rate, the researchers used this model in developing a mobile application.

The researchers developed a model for Doctors Cursive Handwriting with 76% training accuracy and 72% validation accuracy using the remaining 540 images of the data set. This study used Deep Convolutional Recurrent Neural Network and other than the Accuracy, the model is also measured using F1 score. The results are presented in Table 3.

TABLE III. EVALUATION OF THE MODEL

Prescription	Accuracy	F1	Precision	Recall
P1	89	94	95	93
P2	84	91	88	95
P3	67	75	69	83
P4	87	92	88	97
P5	78	86	78	97
P6	82	88	97	80
P7	84	82	88	77
P8	73	79	70	92

Prescription	Accuracy	F1	Precision	Recall
P9	82	88	81	97
P10	80	86	89	84
P11	80	87	91	83
P12	89	91	92	90

It shows that Prescription 3 had the lowest accuracy, as some of the doctors wrote it differently from the preset prescription given, therefore, the machine was unable to learn all of them. For example, the three times a day is written as 3x a day, and there are instances where the doctors write 100 instead of 10 and the dataset the researchers' dataset is limited to learn all the given different ways in writing the prescription 3. Another reason is the problem with the duplicate characters, in the decoded result the double letters were only read by the system as a single letter.

The model is implemented using a mobile application named DCHRS or simply an abbreviation for "Doctors' Cursive Handwriting Recognition System" which aims to identify the medicine name and instructions of use inside the captured image of doctors' cursive handwriting and provide the normal text version of the handwriting.

The researchers tested the prototype on the 540 images and by using the developed model. There are 45 images for each of the twelve (22) prescriptions are fed to the developed model. Each Prescription achieved a different number of images correctly identified prescription by the developed model. The tally of results is displayed in Table 4.

TABLE IV. TALLY OF THE CORRECTLY IDENTIFIED PRESCRIPTION IMAGES BASED ON THE VALIDATION USING THE MOBILE APPLICATION

Prescription	Number of Correctly Identified Images
Prescription 1	39
Prescription 2	35
Prescription 3	26
Prescription 4	37
Prescription 5	30
Prescription 6	26
Prescription 7	38
Prescription 8	23
Prescription 9	34
Prescription 10	32
Prescription 11	29
Prescription 12	40

Based on the results listed there are more correctly recognized input images than the misidentified images

V. CONCLUSIONS AND RECOMMENDATIONS

The study successfully implemented the hybrid model in web and mobile application and based on the testing there are more correctly identified prescriptions than the misidentified. There are 389 images correctly identified out of the 540 input images. The testing through the mobile application yielded a 72% accuracy. To validate the performance of the mobile application for the second time, the researchers wrote the 12 prescriptions, there is a total of 48 handwriting samples were made. Out of the 48 captured handwriting images, there are only 17 images correctly identified by the mobile application DCHRS. For the second validation set, the accuracy of the model implemented in the mobile application is 35%.

This study was able to successfully combine CNN and RNN as a hybrid algorithm to develop a Doctors' Cursive Handwriting Recognition System. The model was able to perform its intended purpose of recognizing script prescription to normal text. The model's implementation in a mobile and web application provided a proof of concept of the proposed hybrid.

This study also proves that some of the characters in the image can be confused to a different character. For example, some of the decoded output shown the letter "o" when originally the cursive letter "a" is what written in prescription image. Another error encountered in this study is with the duplicate character, there are decode result wherein it only shown "thre" instead of "three" this happened because of the issues in encoding. To address this problem the future researchers should introduce a pseudo-character which will be denoted as "-" in the following text. This means that a blank should be inserted between duplicate characters to avoid the neural network to read it as a single character.

For future researchers, the location, lighting, and the distance of the image should be taken into account as it can affect the quality of the image data. It is also recommended to provide more data, especially for prescriptions as it can be written in many ways. If the future researchers still want to pursue using prescriptions as data set during data collection, the researchers should give the doctors lesser time when it comes to writing their samples in order to get more complex or unreadable cursive handwriting and to test how well the model works. Skeletonizing the image is not highly suggested since the model can still work on raw images and skeletonization have its disadvantages. It is recommendable to add more lists of prescriptions to add a wide-range variety of data in the system. Exploring other recognition algorithm is encouraged to be able to compare the accuracy of the recognition.

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