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Recognition of Doctors' Cursive Handwritten Medical Words by using Bidirectional LSTM and SRP Data Augmentation

Shaira Tabassum[1], Ryo Takahashi[1], Md Mahmudur Rahman[2], Yosuke Imamura[1], Luo Sixian[1], Md Moshiur Rahman[3], and Ashir Ahmed[1,2]

[1]Faculty of Information Science and Electrical Engineering, Kyushu University, Japan
[2]Global Communication Center, Grameen Communications, Bangladesh
[3]Graduate School of Biomedical and Health Sciences, Hiroshima University, Japan
Email: tabassum.shaira.264@s.kyushu-u.ac.jp

***Abstract*—Inability to read doctors' handwritten prescriptions causes 7,000 deaths a year in a developed country like the US. The situation should be worse in developing countries where more doctors use handwriting prescriptions. In Bangladesh, the writings become more indecipherable as they contain both English and Bangla words with Latin abbreviations of medical terms. As a result, patients and pharmacists find them difficult to read and the pharmacists provide wrong medicines. In order to ease the difficulty of reading doctors' prescriptions, this paper proposes an online handwritten recognition system to predict the doctors' handwriting and develop a digital prescription. To build this system, the "Handwritten Medical Term Corpus" dataset is introduced which contains 17,431 data samples of 480 words (360 English and 120 Bangla) from 39 Bangladeshi doctors and medical professionals. A bigger sample size can improve the recognition efficiency. A new data augmentation technique SRP (Stroke Rotation and Parallel-shift) method is proposed to widen the variety of handwriting styles and increase the sample size. A sequence of line data is extracted from the augmented image dataset of 1,591,100 samples which is fed to a Bidirectional LSTM model. The proposed method has achieved 89.5% accuracy which is 16.1% higher than the recognition accuracy with no data expansion. This technology can reduce medical errors and save medical cost and ensure healthy living.**

***Index Terms*—Portable Health Clinic (PHC), handwritten medical words, doctors' handwriting, medical prescriptions, bidirectional LSTM, SRP method, data augmentation, online character recognition.**

I. Introduction

World Health Organization (WHO) recommended doctor to population ratio is 1:1000 whereas the ratio is only 0.304:1000 in Bangladesh [1]. According to a global study, physicians in Bangladesh spend 48 seconds to each primary healthcare consultation against 22.5 minutes in Sweden [2]. Consultation time includes listening to patients' complaints, analyzing test reports, writing prescription and explaining suggestions. They want to serve another patient rather than spending time to write a prescription. Fast handwriting becomes cursive and makes it difficult for the readers (patients, pharmacists, nurses) to read. There are cases where the pharmacists misread the prescriptions and provide wrong medicines. According to a study by Bhuiyan et al. [3], incapability of understanding doctors' prescription is a barrier of getting effective health services in Bangladesh. A report from National Academies of Science Institute states that doctors' sloppy handwriting causes 7,000 deaths annually even in a developed country like US [4]. Doctors can be trained to write readable prescriptions, but they get a very short time to counsel each patients. Thus, we took the machine learning approach to assist the doctors by recognizing doctors' cursive handwriting word by word and digitize them in readable texts. The research is conducted in several steps: data collection for recognition, data preprocessing for simplification, data augmentation for increasing data size, developing machine learning model, and training the model to estimate handwritten medical terms.

There are few Enlgish handwriting datasets available online such as IAM Handwriting Database by University of Bern [12] and HP_DocPres by Dibyajyoti et al. [13]. IAM Handwriting Database is one of the largest and most popular dataset of english handwritings, but it doesn't contain medical terms. HP_DocPres is a doctors' prescription dataset to classify printed and handwritten texts, but the dataset is not labelled. Fajardo et al. has introduced a doctors' handwriting dataset with 1,800 samples from 12 prescriptions, but the samples are available only in English [9]. However, prescriptions in Bangladesh contain a mixture of both English and Bangla words [3]. Therefore, this research introduces 'Handwritten Medical Term Corpus' dataset to recognize Bangladeshi doctors' writings. Initially, a corpus of medical words from Bangladeshi prescriptions are collected from the Portable Health Clinic (PHC). PHC is a telehealthcare system for preventing non-communicable diseases (NCDs) by providing affordable health services to the rural people of developing countries [14] [15]. PHC has an online database which contains digital prescriptions of 8,324 patients. Considering the most frequently appeared words in the prescriptions, a 'Medical Term Corpus' from PHC prescriptions is created which has 480 words (320 English and 120 Bangla). Afterwards, these 480 words were shown to 39 physicians and healthcare professionals to contribute their handwritings. This way, we collected 17,431 handwritten data samples.

In order to recognize various types of handwriting styles, data needs to be collected from plenty of sources which is both time consuming and costly. However, data augmentation is a good way to deal with this problem [16]. In this paper, a new data augmentation technique SRP (Stroke Rotation and Parallel-shift)

TABLE I: Comparison and analysis among related handwriting recognition systems

SL	Handwriting Recognition	System Architecture	Dataset	Data Augmentation	Accuracy
1.	Bangla characters [5]	Lightweight CNN	BanglaLekha - 1,66,105 CMATERdb - 63,351 ISI - 54,265	Shifting, rotation and zoom in	98.00% 96.81% 96.40%
2.	English characters [6]	LeNet-5 CNN	UNIPEN - 26,163	-	93.70%
3.	Chinese characters [7]	Deep CNN	CASIA - 3.9 million	DropStroke	99.52%
4.	Chinese characters [8]	RNN(LSTM & GRU)	CASIA - 3.9 million	DropStroke	98.15%
5.	Doctors' handwriting (english) [9]	CRNN	Doctors' handwriting - 1,800	-	72.00%
6.	Doctors' handwriting (english) [10]	CRNN	Short handwritten texts	-	98.00%
7.	Bangla words [11]	Bidirectional LSTM	Handwritten words - 65,620	-	79.00%

SL	CC	Drugs				Advices	Test
1	Low back pain,	Tab - Naprosyn - 500 mg - 1+0+1	After meal		5 Days	Previous rules will continue to medication, Do not work long being bent , Use high commode , Take plenty of water , Avoid lifting weights, Please	S.creatinine ,
		Tab - Beklo - 5 mg - 1+0+1	After meal		5 Days		
2	headache, low back pain, acidity, constipation.	Tab - Neoceptin-R - 150 mg - 1+0+1	Before meal		15 Days	Take plenty of water , Do not work long being bent , Avoid lifting weights, Avoid foods that are high in fat and contain higher amount of oil and spices, Please consult with Eye specialist.	
		Tab - Ace - 500 mg - 1+1+1	After meal		3 Days		
		Tab - Calbo D - - 0+0+1	After meal		Cont.		
		Syp - Avolac - - 1 tea spoon	After meal	3 times -- if constipation.			
3	DM on insulin					the Diabetic food-chart, Please check blood sugar fasting and before dinner. then adjust the dose of insulin.	

Fig. 1: Sample of PHC prescription data

method is proposed to create multitudes of handwriting styles. SRP method considers each stroke of words and generates new data by changing the coordinates. The extended dataset contains 1,591,100 data samples which have been augmented using the SRP method. There are several data augmentation methods for handwriting to widen Arabic and Chinese handwritten characters [16] [7].

Convolutional Neural Network (CNN) is widely used for offline handwriting character recognition. Several works have been done with high accuracy by transforming the data in image-like representation [7] [5] [6]. However, Recurrent Neural Network (RNN) has recently become very popular for handwriting recognition where sequential data is used instead of generating image-like representation [9] [10] [8]. Sequence data can contain rich information of handwriting data than static images [8]. Thus, this research has extracted a sequence of line data from the handwritten dataset to feed a RNN model. A bidirectional LSTM model is developed as it considers both past and future states simultaneously for making predictions. The system has achieved 89.5% accuracy with SRP data augmentation method. The accuracy gets 73.4% without applying SRP expansion method. A comparison among similar related works is given in TABLE I.

The rest of the article is organized as follows. Section II introduces the 'Handwritten Medical Term Corpus' dataset and data collection process. Section III presents the steps for handwriting recognition and introduces our proposed SRP data augmentation method. Section IV demonstrates experimental analysis and results. And finally we conclude our contributions with limitations and areas of improvements in Section V.

II. Dataset: Handwritten Medical Term Corpus

This research develops a primary 'Handwritten Medical Term Corpus' dataset containing 480 English and Bangla handwritten medical words. The data collection process is described below.

A. *Corpus creation from digital prescriptions*

The PHC system has an online database which preserves all the health information of their patients. The online database contains five types of data: i) survey data ii) registration data iii) clinical data iv) conversation data and v) prescription data. The main part of the dataset used in this research is collected from the 'prescription data' of PHC. An example of PHC prescription data is given in Fig. 1.

The PHC dataset contains digital prescriptions of 8,324 people. The prescription data has several columns such as medicine names, symptoms, advices. This research has created a corpus of medical words using the most frequently appeared words in the PHC prescription data. There are 360 English words from medicine names column and 120 Bangla words from advices column in Medical Term Corpus. Words are sorted with how many times they appeared in the prescriptions, as in Fig. 2.

B. *Handwritten data collection using android application*

An android application is developed to collect handwritten medical words. The application displays medical words from

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426,Ostocal D
381,Maxpro
376,Ranitid
367,Napa
322,Ferocit
285,Neuro B
278,Comet
261,Omidon
261,Multivit plus
261,Calbo D
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Fig. 2: Sample of Medical Term Corpus

'Medical Term Corpus' one by one and a data provider provides their handwriting of the given medical term. Samsung Galaxy Tab S3 is used for the data collection as the tablet contains one stylus pen. The data providers have used the stylus pen to provide their handwriting on the tablet. The application also receives pen movements in xy-coordinates and pen status such as the pen is up or down, and stores these information in the database as sequential data. Both the original corpus data and the handwritten word are also stored in the database 'Handwritten Medical Term Corpus'. The corpus data is used as true value or correct answer for machine learning model and handwritten data is used to train the model to recognize handwritten medical terms. Fig. 4 demonstrates the whole data collection process.

C. Data Profile

'Handwritten Medical Term Corpus' contains 480 medical words (360 English and 120 Bangla). These 480 words are selected as most frequently appeared medical words in 8324 prescriptions of Bangladesh. The handwritten data is collected from 39 doctors and medical professionals. 12 of the data providers gave incomplete data which caused 1,289 missing data. Thus, the dataset contains 17,431 handwritten images of 480 medical words.

III. Recognition Methodology

After collecting the data samples, the research has been conducted in three steps, as shown in Fig. 3. First of all, the sample handwritten data are analyzed and preprocessed. Then, a new data augmentation method is applied on the preprocessed images to increase the number of data samples. In these steps, a sequence of line data is extracted both from the original and the augmented image data. Finally, the sequence data is fed to a bidirectional LSTM model as input for estimating handwritten medical terms.

A. Data Pre-processing

Instead of using image-like representation for handwriting samples, rich knowledge such as spatial and temporal information can be collected from the raw data. The collected information can be represented as a sequence of variable length [8]. The sequence is given in equation (1) where x_i and y_i states the xy-coordinates of pen movements and s_i is the stroke number of point i.

$$[[x_1, y_1, s_1], [x_2, y_2, s_2], ..., [x_n, y_n, s_n]] \tag{1}$$

The preprocessing block has three segments. The first two segments simplify the image data by removing repetitive and nearby points. The third segment generates a six-dimensional vector sequence for each stroke which can be passed into an LSTM model. The preprocessing segments are described below:

1) Removing Redundant Points: Handwriting style differs from person to person even in the same language. Different people have different handwriting habits such as regular, cursive, small. As a result, each person creates different sampling points while writing the same character. Thus, removal of redundant points in handwritten data has become an essential part of data preprocessing for further estimation. To remove redundant points, lets assume a particular point (x_i, y_i, s_i) where $s_i = s_i + 1 = s_i - 1$. Removal of point i depends on two conditions:

i. Distance between points: Point i should be removed if the distance between point i and point $i-1$ is very small, as given in equation (2). Here, the threshold $T_{dist} = 0.005 * max(H, W)$, where H and W indicates the vertical and horizontal widths of the user input place. Any connecting point i between two points $i+1$ and $i-1$ on a straight line should also be removed.

$$\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} < T_{dist} \tag{2}$$

ii. Cosine similarity: Cosine similarity measures similarity between two non-zero vectors of an inner product space. If the similarity between point i and $i-1$ is more than the cosine angle threshold between them, the point should be removed, as given in equation (3). Here, the threshold T_{cos} is set to 0.99.

$$\frac{\Delta x_{i-1}\Delta x_i + \Delta y_{i-1}\Delta y_i}{(\Delta x_{i-1}^2 + \Delta y_{i-1}^2)^{0.5}(\Delta x_i^2 + \Delta y_i^2)^{0.5}} > T_{cos} \tag{3}$$

Point i is removed if any one of the given two conditions is satisfied. By removing the redundant points, the shape of the character is well preserved and each point of the new sequence becomes more informative [8]. Fig. 5 is an example of the whole process on a sample handwritten medical term.

2) Normalization: To simplify the input data, the data is normalized in this step. For x coordinate, the maximum x_{max} and the minimum x_{min} are extracted from all the data points. Then, a certain x coordinate X is normalized to X_{nor} using equation (4).

$$X_{nor} = \frac{X - x_{min}}{x_{max} - x_{min}} \tag{4}$$

This calculation is also performed to y coordinate, and as a result, (x, y) coordinates data is scaled to have a value between 0 and 1.

3) Generating Sequence Data: After preprocessing, the research has created straight line data by connecting two normalized points. Then, a six-dimensional representation is extracted for each straight line L_i with the connecting points i and $i+1$, as given in equation (5).

$$L_i = [x_i, y_i, \Delta x_i, \Delta y_i, I(s_i = s_{i+1}), I(s_i \neq s_{i+1})] \tag{5}$$

Here, x_i and y_i states the start position of the line as xy-coordinates. Δx_i and Δy_i are the direction of the pen movements in x-axis and y-axis direction. The last two terms determine the pen status where $[0, 1]$ means pen-up and $[1, 0]$ means pen-down. $I(s_i = s_{i+1}) = 1$ indicates the start and end points of

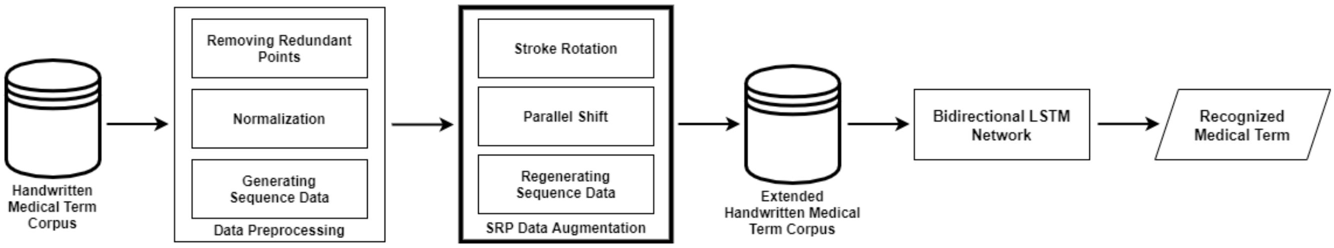


Fig. 3: Block diagram of handwritten medical words recognition system

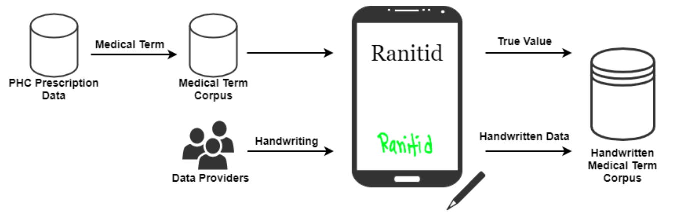
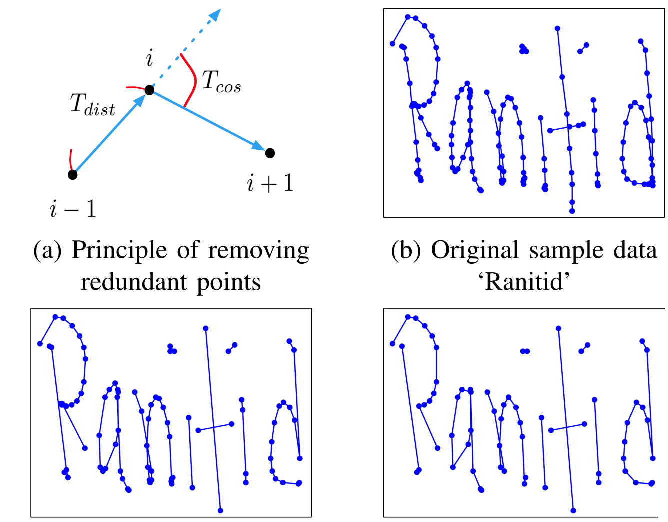


Fig. 4: Data collection process of Handwritten Medical Term Corpus



(a) Principle of removing redundant points (b) Original sample data 'Ranitid'

(c) After removing connecting points on straight line (d) After removing points cl to next points

Fig. 5: Removing redundant points from handwritten data

the straight line are on the same stroke and $I(s_i \neq s_{i+1}) =$ means that the straight line moves to the next stroke. Thu the (x, y, s) coordinate is transformed into a new sequence c $[L_1, L_2, ..., L_{n-1}]$. For simplification, this sequence is denote as $[x_1, x_2, ..., x_k]$. Here, each x_i represents a six-dimension vector [8].

B. Data Augmentation

This research has applied data augmentation on the prepr cessed images in order to expand the data size of 'Handwri ten Medical Term Corpus'. For data augmentation, the SR Method (Stroke Rotation and Parallel-shift) is proposed in this paper. SRP method expands the quantity of data by rotating and shifting the strokes parallelly. This method specifically targets handwritten types of data and can widen the variety of handwriting styles.

1) Stroke Rotation: First, the middle point of a stroke is calculated from the coordinates of the start and end points for each image. Then, all the points on the stroke are rotated around the middle point. It causes rotation of the stroke as well. Fig. 6(a) demonstrates the principle of Stroke Rotation of SRP method. By considering (x_f, y_f) as the starting point and (x_l, y_l) as the ending point of a stroke, equation (6) can calculate the middle point of a stroke (a, b).

$$(a, b) = (\frac{x_f + x_l}{2}, \frac{y_f + y_l}{2}) \tag{6}$$

To rotate a certain point (x, y) to θ around (a, b), equation (7) is used. Here, (X, Y) is the rotated point.

$$\begin{pmatrix} X-a \\ Y-b \end{pmatrix} = \begin{pmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{pmatrix} \begin{pmatrix} x-a \\ y-b \end{pmatrix} \tag{7}$$

The stroke itself rotates θ around the middle point of the stroke by applying this equation to all the points on the stroke. Fig. 6(b) shows the example of a word before applying Stroke Rotation in blue color, and red one represents the rotated word. This technique is applied to each stroke with different angle in ind words from the

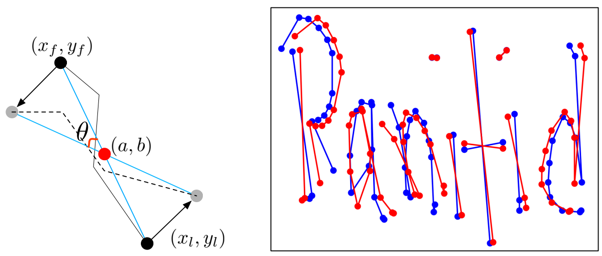


Fig. 6: (a) Principle of Stroke Rotation, (b) Sample data after preprocessing (blue) and after applying Stroke Rotation (red)

2) Stroke Parallel-shift: A constant number (x, y) is added to each of the coordinates of the points on a stroke which shifts the stroke itself parallelly. Fig. 7(a) explains the principle of Stroke Parallel-shift. Equation (8) shifts a point on a stroke (x, y) to (X, Y).

$$(X, Y) = (x + dx,\ y + dy) \tag{8}$$

By applying this equation to all the points on the stroke, the stroke itself is shifted by (dx, dy). Fig. 7(b) shows the example of a word before applying Parallel-shift in blue color, and red one represents the shifted word. This technique is applied to each stroke with different values of dx and dy in order to create different shape of letters and words from the original data.

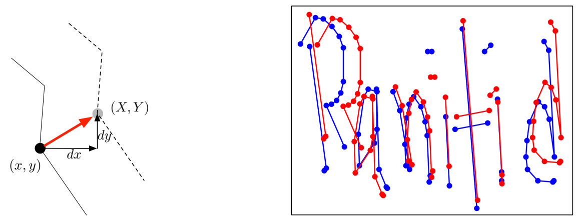


Fig. 7: (a) Principle of Parallel-shift, (b) Sample data after preprocessing (blue) and after applying Parallel-shift (red)

3) Regenerating Sequence Data: After applying SRP method, the six-dimensional representations for all the new augmented images have been generated by updating the values of x_i, y_i, Δx_i and Δy_i with the values of dx, dy and θ. However, SRP method doesn't change the values of $I(s_i = s_{i+1})$ and $I(s_i \neq s_{i+1})$. Equation (9) states the six-dimensional representation for the new images created by SRP data augmentation method.

$$L_i = [x_i + dx,\ y_i + dy,\ \Delta x_i + \theta,\ \Delta y_i + \theta, \\ I(s_i = s_{i+1}),\ I(s_i \neq s_{i+1})] \tag{9}$$

C. Machine Learning Model: Bidirectional LSTM

Handwritten data usually contain multiple strokes with numerous points. Moreover, writing speed, order, character shape information are also preserved in sequential data. These valuable information are difficult to get from static images. Thus, this research deals with raw sequential data instead of generating image-like representations to get the richer information about doctors' handwriting.

In order to develop complete end-to-end recognition, Bidirectional LSTM is used on the sequential line data extracted from the augmented handwritten images. Fig. 8 explains the concept of Bidirectional LSTM. Bidirectional LSTM uses past inputs and future inputs to calculate the parameters while the original LSTM uses only past inputs for the calculation [17]. The augmented sequence of line data is used to train the model. Bidirectional LSTM uses both the past and the future line data to write the current line data for the parameter calculation. Thus, the model has preprocessed sequential data for training and estimates the given medical word.

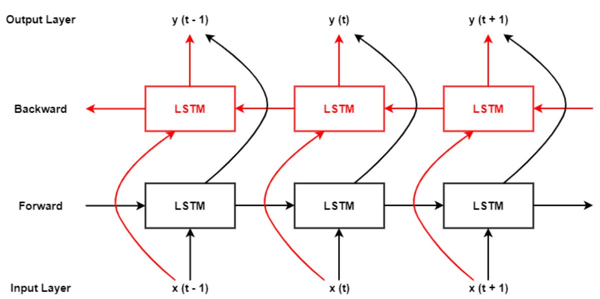


Fig. 8: Concept of Bidirectional LSTM

Fig. 8 presents the architecture of the bidirectional LSTM used for this research which is built using Keras, a neural network library of python. The maximum length of the data is set to 260. In order to fix this length, zeroes are padded to the end of each data. The number of hidden units of LSTM layer is set to 300 and pooling layer is included after the LSTM layer. Dropout is fixed between pooling and dense layer to avoid overfitting [18]. Early Stopping is also applied as the same data is learned many times by increasing the number of data size [19]. The architecture has the following parameters:

- Activation function: Softmax [20]
- Loss function: Categorical cross-entropy [21]
- Optimization function: Adam [22]
- Learning rate: 0.001 [23]
- Batch size: 512 [23]
- Number of epochs: 5 [23]
- Dropout: 0.3 [18]

keras.layers.wrappers.Bidirectional(LSTM)	Input:	(None, 260, 6)
	Output:	(None, 300)
Dropout = 0.3		
keras.layers.Reshape	Input:	(None, 300)
	Output:	(None, 300, 1)
keras.layers.AveragePooling1D	Input:	(None, 300, 1)
	Output:	(None, 150, 1)
Dropout = 0.3		
keras.layers.Dense	Input:	(None, 150)
	Output:	(None, 200)
keras.layers.Dense	Input:	(None, 200)
	Output:	(None, 480)

TABLE II: Bidirectional LSTM model architecture for doctors' handwritten medical terms recognition

IV. Results and Discussion

'Handwritten Medical Term Corpus' has 17,431 instances of 480 medical words which are collected from 39 doctors and medical professionals. As 12 data providers provided incomplete data, there are 12 incomplete and 27 complete sets of data. Three words are randomly selected for each sample as test data from the 27 complete sets of data. After selecting three sets of test data, the remaining 36 sets are used as train data. Thus, train data size is 15,911 and test data size is 1,440 (3 sets of 480 words).

In data augmentation, the stroke rotation process is performed 10 times on each data which increased the data size from 15,911 to 159,110. Then, parallel-shift is performed 10 times on each data which was previously expanded by rotation. Thus, the 'Extended Handwritten Medical Term Corpus' dataset has 1,591,100 train samples and 1,440 test samples (no expansion). The train data has been divided into train and validation set at the ratio of 9:1. By repeating this process 10 times, the effectiveness of the model is evaluated based on the average value of accuracy, variance and standard deviation on the test samples. The number of epochs is set to 5 and the mini-batch size is set to 512. The training data is shuffled to create a different mini-batch for each epoch.

The research has also trained the bidirectional LSTM model without using SRP expansion to evaluate the performance of the proposed method. In that evaluation, number of epochs is set to 100 and the mini-batch size is set to 64. TABLE III shows the results of the handwritten word recognition test with and without

TABLE III: Handwritten recognition system model evaluation

Evaluation target	Before applying SRP	After applying SRP
Sample size	15,911	1,591,100
Accuracy (mean)	73.4%	89.5%
Accuracy (median)	83.7%	91.4%
Variance	5.3 x 10^{-2}	5.7 x 10^{-3}
Standard Deviation	2.3 x 10^{-1}	7.5 x 10^{-2}

data expansion. The average accuracy without data expansion is 73.4% whereas the accuracy with SRP data expansion is 89.5%. Even without data expansion, the accuracy is relatively high but the impact of test data collection is very large. On the other hand, when the data is expanded, the accuracy is stable as a whole. The standard deviation is also smaller when the data is expanded. The reason is that there are a lot of over-learning when the data is not expanded.

V. Conclusion and Future work

This paper reported an idea to use machine learning approach to recognize doctors' handwriting and translate them into readable digital text. A 'Handwritten Medical Term Corpus' dataset was created with 17,431 handwritten data of 480 English and Bangla medical words. SRP, a data augmentation method was introduced to increase the size of the data sets. An online character recognition system using bidirectional LSTM for predicting doctors' handwriting was used. The medical corpus dataset was generated from the digital prescriptions of PHC. Bidirectional LSTM was used for making the predictions. We calculated the accuracy and it was 16.1% higher than the recognition accuracy without data expansion.

SRP method can be used for other datasets as long as characters are collected as time-series data of coordinates. If these datasets are expanded and converted to image data, they can also be used for data expansion of offline characters. In future, new data expansion methods will be applied such as changing the character ratio to improve the recognition rate. As this research has used fixed parameter values in the bidirectional LSTM model, the adjustment of parameters is also required to improve the performance of the model. In order to recognize doctors' handwriting with higher accuracy, more medical words and associate recognized terms with prescriptions will be dealt with by using a larger medical term corpus.

The proposed doctors' handwriting recognition system will make it possible to reduce medical errors and save medical cost and ensure healthy living.

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