An Autonomous Learning System of Bengali Characters Using Web-Based Intelligent Handwriting Recognition

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Abstract

This study aims to develop an intelligent Bengali handwriting education system to improve the literacy level in Bangladesh. Due to the socio-economical limitation, not all of the population has the chance to go to school. Literacy in Bangladesh is a key factor for socio-economic progress, and the Bengali literacy rate grew to 61.5% in 2015 from 5.6% in 1947. According to this statistics, the male literacy is 64.6% and the female literacy is 58.5%. The gender literacy difference is about 6.1% where female literacy rate is less than male literacy rate [Bangladesh Literacy Survey Report by UNESCO, 2015]. Despite government programs, the literacy rate was improved very sluggishly, only about 10 times within 60 years. Although the government has various educational activities, the number of schools was not adequate yet. Considering this educational background, traditional handwriting teaching system is not enough to improve the Bengali literacy rate at 100%. There are three major drawbacks in traditional handwriting teaching system, such as time-consumption, faultiness, teacher-oriented. It motivated us to develop a web-based (browser of computer or smartphone such as iPhone and Android) intelligent handwriting education system for autonomous learning of Bengali characters. Our education system can ensure the learning of Bengali characters at anywhere at any time for those population, who do not have chance to go to school, especially children, women and elderly people. Thus, our proposed education system can help to achieve 100% literacy improvement within a very short period, and woman advancement can also be established through education. To the best of our knowledge, this is a pioneering attempt for the development of web-based intelligent handwriting education system to improve Bengali literacy rate.

In this research, we developed a prototype of web-based (browser of computer or smartphone) intelligent handwriting education system for autonomous learning of Bengali characters. It allows students to do practice their handwriting at anywhere at any time. As an intelligent robot tutor, the system can automatically check the handwriting errors, such as stroke order errors, stroke direction errors, stroke relationship errors, and immediately provide

colorful error feedbacks to the students to correct by themselves. Bengali is a multi-stroke input characters with extremely long cursive shapes where it has stroke order variability and stroke direction variability. Due to this structural limitation, recognition speed is a crucial designing issue to apply traditional online handwriting recognition algorithm. Fundamentally, multi-stroke recognition algorithm results very slow recognition speed in case of long cursive characters like Bengali or Japanese Hiragana. For this reason, existing multi-stroke recognition algorithms are not applicable for the development of web-based Bengali handwriting education system, because it needs to provide the real-time students feedback. To address this problem, we have developed hierarchical online recognition algorithm to improve the recognition speed with considerably higher accuracy. We have also developed a predefined structural dictionary using the structural information of Bengali characters. Using this structural data, our algorithm can identify the handwriting errors automatically and feedback to students together with recognition results. Our proposed web-based Bengali handwriting education system can also be named as intelligent robot tutor. Here, the students can learn by using our autonomous learning methodology without the teacher supervision and they can correct the committed errors by themselves. In addition, the students can repeat the same exercise for several times to speed up the learning process. Thus, the learning process becomes much more effective.

The experimental analysis of design data set have confirmed that our proposed hierarchical recognition algorithm improved the average recognition accuracy up to 95% as well as recognition speed of 40ms/character. It makes our recognition algorithm adaptable for the application of web-based language learning. Finally, we have conducted a survey in Bangladesh for the performance analysis of our proposed education system and collected test data set. The analytic results of surveyed data have confirmed that our proposed web-based Bengali education system was highly appreciated by the illiterate people in Bangladesh, especially for children, women and elderly people. The experimental results showed that our autonomous learning methodology helped to improve the average recognition accuracy by 4.1% (from 87.2% to 91.4%). Moreover, the total average of Mean-Opinion-Score (MOS) for all aged people has the value of 4.1 with the standard deviation of 0.7. This value ensured that almost every user evaluated our system as "Good" (Score 4), where the student's evaluation score is defined as 1 (Bad), 2 (Poor), 3 (Fair), 4 (Good), and 5 (Excellent).

Our analytic results have confirmed that the application of autonomous learning methodology will be very effective and the successful use of web-based Bengali handwriting education system can help for literacy improvement in Bangladesh within a very short period. We want to promote our slogan as "one web-based Bengali education system can help to improve up to 100% literacy of Bangladesh in near future; education is the only solution, education first." In future, we will focus our research to apply the proposed hierarchical algorithm for other cursive characters like Japanese Hiragana and Katakana learning. Thus, this research project helps to create deepest friendship between Japan and Bangladesh. Furthermore, we will focus our research on the development of Bengali handwriting education system considering Bengali syllabic and compound characters (consonants & vowels combined shape) to support Bengali word learning.

Keywords: autonomous learning, web-based intelligent handwriting education, hierarchical recognition algorithm, automatic stroke error detection, web-based client-server interface

Contents

1 INTRODUCTION

1.1 Motivation and Our Contribution

Literacy in Bangladesh is a key for socio-economic progress, and the Bengali literacy rate grew to 61.5% in 2015 from 5.6% at the end of British rule in 1947. Despite government programs, the literacy rate was improved very sluggishly, only about 10 times within 60 years [Bangladesh Literacy Survey Report by UNESCO, 2015]. Figure 1.1 shows the analysis of Bangladesh literacy improvement with or without using IT autonomous learning methodology.

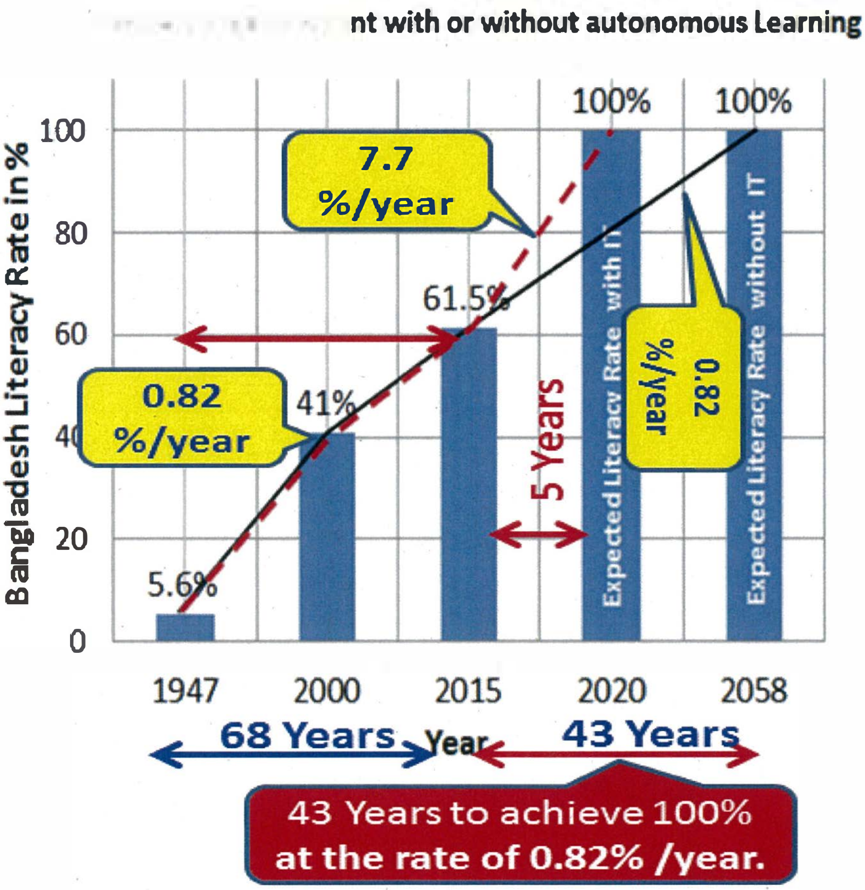


Figure 1.1: Analysis of Bangladesh literacy improvement with or without using IT autonomous learning.
(Literacy data are based on Bangladesh Bureau of Statistics)

Because of socio-economical limitation, all of the population, especially children and older people, do not have the chance to go to school. Although Government has various educational activities, the number of school was not adequate yet. Considering this educational background, traditional handwriting teaching system is not enough to improve the Bengali literacy rate at 100%. As shown in Figure 1.1, if we used only traditional education system, it may expect to achieve 100% literacy in 2058. However, if we consider IT autonomous learning methodology then 100% literacy rate can be achieved within very short period, according to our assumption it can be achieved in 2020. Because, in the traditional handwriting teaching system, the teacher must write a Bengali character on the blackboard and the students should rewrite the handwritten character on their copy notebooks. After that, the teacher tries to check the handwriting errors in the student's notebooks and provides a feedback in the next time, because it's impossible for a teacher to verify and check every student's handwriting in the limited time of the lesson. This system can be successfully acquired only though practice regularly and for long periods. In this context, Hu et al. (2009) defined three drawbacks of the traditional education, such as time-consumption, faultiness, teacher-oriented. In addition, these techniques have many more drawbacks in aspects of socio-economical view point. It motivated us to develop web-based intelligent handwriting education system for autonomous learning of Bengali characters. The learning process becomes much more effective, if the handwritten character is checked just after the students have finished their handwriting. On the other hand, the students can learn without the teacher supervision and they can correct the committed errors. Also, the students can repeat the same exercise several times to speed up the learning process.

In this research project, we are aiming to develop a web-based (iPhone/smartphone or computer browser) intelligent handwriting education system that can ensure the learning of Bengali characters at anywhere at any time for those population, especially children or older people, who do not have chance to go to school. Thus, 100% literacy improvement can be established within a very short period. To the best of our knowledge, this is a pioneering attempt for the development of web-based intelligent handwriting education system to improve Bengali literacy rate (Nazma et al., 2014; Nazma et al., 2016).

Bengali is a multi-stroke input characters with extremely long cursive shaped where it has stroke order variability and stroke direction variability. The difficulty in online recognition of handwritten Bengali characters arises from the facts that this is a moderately large symbol set, shapes are extremely cursive even when written separately. In addition, there exist quite a few groups of almost similar shape characters in their handwritten format. Fundamentally, multi-stroke recognition algorithm results very slow recognition speed in case of long cursive characters. For the structural limitation of Bengali characters, existing multi-stroke recognition algorithm is not applicable for the development of Bengali handwriting education system, because it needs to provide the real-time students feedback. To address this problem, we have developed hierarchical online recognition algorithm to improve the recognition speed with considerably higher accuracy. It makes our system adaptable for web-based language learning and ensured immediate feedback about student's handwriting errors. In this hierarchical online recognition algorithm, we applied a series of matching filters to reduce a small number of candidates characters for final Dynamic Programming Matching (DPM) where local features (angular feature) are used to guide DPM. Then, the character with lowest matching cost is selected as recognition results. Finally, it returns the recognition results. Using the structural information stored in a predefined structural dictionary, our algorithm can identify the handwriting errors automatically and feedback to students together with recognition results. Here, we have modified the traditional DPM algorithm that allows writing speed free variability and improve the recognition accuracy.

1.2 Dissertation Structure

We organized this thesis paper as follows. In chapter 1, we discussed the introduction of our research including Motivation and Our Contribution, Dissertation Structure, Related Prior Studies on autonomous learning method and its different applications. Chapter 1 is also focused on Overview of Bengali Script, Overview of On-Line Handwriting Recognition and the Overview of E-Learning. Chapter 2 describes the Bengali handwriting education system design and implementation. Here we represent the detail of recognition system architecture. Chapter 3 presents learning system evaluation using test and design data set. Finally, Chapter 4 concludes this dissertation with directions of future work.

1.3 Related Prior Studies

In recent years, several research efforts have been done on e-learning system (Hiekata et al., 2007; Tang et al., 2006; Zein et al., 2007; Abdou et al., 2010; Ahmad et al., 2010) which aims to guide students to get more useful advice in their autonomous learning. They had developed an intelligence tutoring learning method to provide autonomous learning environment to the students. With the development of pen-based devices, it is now possible to apply e-learning techniques to handwriting education. Several handwriting education systems have been provided for different languages such as: Chinese, Latin and Arabic. It can be organized on three categories: read only systems, guided ones and systems with automatic errors detection. In case of Chinese handwriting education systems, the work proposed in (Tang et al., 2006) can find both the stroke production error and stroke sequence error but they did not consider the spatial relationship errors. In recent years, some researches on intelligent robot tutoring system has also been done where a robot teacher was used for autonomous learning (Deanna et al., 2015).

To develop a web-based handwriting education system for learning of handwritten Bengali characters, we need to develop an online recognition algorithm for cursive Bengali characters. Extensive research on cursive handwriting recognition has been done during the last few decades for different languages. However, there has not been much work on handwriting recognition of Indian scripts. Particularly, there have very few attempts for the recognition of online Bengali handwritten characters (Bhattacharya et al., 2008; Parui et al., 2008). But both of these two approaches are not applicable for the development of web-based handwriting education system, because of slow recognition speed. In our proposed education system, we have developed efficient hierarchical online recognition algorithm to speed up our system. Here, the student can practice their writing on the digital tablet accessed from both of iPhone/smartphone or computer browser. Then, our recognition engine can analysis the student's handwriting input and checks the handwriting errors to provide useful feedbacks (Nazma et al., 2014; Nazma et al., 2016).

1.4 *Overview of Bengali Script*

Bengali is official language/script of Bangladesh and used by 211 million people of India and Bangladesh. It is also second most popular language/script in India and 5th most popular language in the world. Bengali, like other major Indian characters, is a mixture of syllabic and alphabetic scripts. It came from the ancient Indian script, Brahmi. The concept of upper/lower case is absent here and the direction of writing policy is left to right. Examples of Bengali characters are shown in Table 1.1. Bengali language consists of 50 basic characters including 11 vowels and 39 consonants. In Bengali basic characters (chad) is a nasalization marker that appears over the top of an independent vowel or consonant. In our experiment, we considered 49 basic Bengali characters except (chad). Most of the characters in Bengali language have a horizontal line at the upper part. We call this line as head-line or matra. Vowels have their modified shapes called Vowel Modifiers (VM). In Bengali script a vowel following a consonant takes a modified shape. Depending on the vowel, its modified shape is placed at the left, right (or both) or bottom of the consonant. These modified shapes are called modified or syllabic characters. In Bengali, there have 10 vowel modifiers which are joined with 35 of consonants and make 350 modified syllabic Bengali characters. On the other hand, several consonants or a vowel in conjunction with a consonant form a large number of possible different shapes, called compound characters. However, in the present day Bengali text, the occurrence of compound characters is less than 5% and the rest is only basic characters and vowel modifiers. So, our proposed autonomous learning system is focused on the learning and recognition of Bengali basic characters.

Table 1.1: Different shape of 50 Bengali basic characters where 49 of them are used in our recognition experiment

Type	Characters	Number of Characters	
Vowels	অ(a) আ(aa) ই(i) ঈ(ii) উ(u) ঊ(uu) ঋ(ri) এ(e) ঐ(ai) ও(o) ঔ(au)	11	50 49*
Consonants	ক(ka) খ(kha) গ(ga) ঘ(gha) ঙ(nga) চ(ca) ছ(cha) জ(ja) ঝ(jha) ঞ(nya) ট(tta) ঠ(ttha) ড(da) ঢ(dha) ণ(na) ত(ta) থ(tha) দ(da) ধ(dha) ন(na) প(pa) ফ(pha) ব(ba) ভ(bha) ম(ma) য(ya) র(ra) ল(la) শ(sha) ষ(ssa) স(sa) হ(ha) ড়(rra) ঢ়(rha) য়(yya) ৎ(khandata) ঃ(visarga) ং(anus -vara) ঁ(chad)*	39 38*	

* We considered 49 basic Bengali characters except (chad) in our experiment.

1.4.1 History of the Bengali Script

The modern Bengali alphabet has undergone a long evolution. The Bengali script evolved from the Siddhaṃ script, which belongs to the Brahmic family of scripts, also known as Sanskrit. Sanskrit was spoken as a secular language in Bengal since the first millennium BCE. Sanskrit was the standardized form of Old Indo-Aryan. It shared similarities with other classical Indo-European languages, including Ancient Greek, Persian and Latin. During the Gupta Empire, Bengal was a hub of Sanskrit literature [26]. The Middle Indo-Aryan dialects were spoken in Bengal in the first millennium when the region was a part of the Magadha Realm. These dialects were called Magadhi Prakrit. They eventually evolved into Ardha Magadhi. Ardha Magadhi began to give way to what are called Apabhramsa languages at the end of the first millennium.

A large number of ancient epigraphic records and manuscripts have been discovered from different parts of Bengal, which have supplied important information to reconstruct the historical origin and development of the modern Bangla alphabet.

By virtue of the direction of writing, ancient Indian scripts are divided mainly into two parts, the Brahmi and the Kharoshthi. The Kharosthi was written from the right to the left, while the Brahmi left to the right. The ancient Indians took the Kharosthi alphabet from the Aramaic script. But this script was mainly limited in the North-West frontier of India. It spread over other parts of India during the Kusana period. A number of Kusana coins, which have been discovered from Bengal, bear the Kharosthi script. Besides these, a number of terracotta seals and fragment potsherds have been discovered from Chandraketugarh and Bedachapa in West Bengal, which bear also the Kharoshthi alphabet. But the Kharoshthi alphabet has not made any contribution to the development of the Bangali alphabet.

The modern Bangla alphabet originated from the ancient Indian Brahmi script, which was the oldest and popular script of India. The discovery of the Indus valley writing has led some scholars to guess that Brahmi was locally developed out of the Indus valley writing system. But no one has been able to demonstrate how this evolution took place. Some scholars are of the view that it was borrowed from outside of India. But there is no definite proof about this assumption. Actually, it was a significant contribution of the ancient Indian people who invented Brahmi scripts and their own numerals. The Indians used to believe that the Brahmi originated from the creator Brahma and hence, this hence the script has been named Brahmi. On the other hand, it is assumed that as the Brahmi was the alphabet of the Brahman, it has been named as Brahmi. The most ancient written record of Brahmi was discovered on a vase at Piprahwa (487 BC), Tarai in Nepal.

But Brahmi script had widely been incised in the stone pillars and stone slabs of the great Mauryan King Ashoka. We get the complete form of Brahmi in the Asokan rock edicts. In this connection, it may be imagined that the Brahmi made a long way of evolution to come to this form of Asokan stage. But it is interesting to note that in course of time the Indians had forgotten to read and write the Brahmi alphabet. It is stated that once Firuzshah Tughlaq, the sultan of Delhi, collected a pillar inscription of Asoka and called upon the scholars around him to decipher it. But nobody was able to do it. In 1837, James Prinsep, a British scholar, was able to read the Asokan Brahmi successfully, which paved the way for deciphering other ancient Indian Proto-regional Brahmi. Some epigraphic records of Bengal were deciphered during the last half of the 19th century. But a large number of the early Bengal inscriptions were deciphered and published within the first half of the 20th Century. On a close observation, the forms and variations of the alphabets of those huge epigraphic records of Bengal, it has been possible to trace the historical development of the Bangla alphabet.

Bangla as well as other modern Indian alphabets such as Nagari, Sarada, Tamil, Telegu, Kanedi, Gujrati, Grantha, Gurumukhi, Malaya, Tibbeti are the present form of local development of the Brahmi alphabet. With the passage of time the writing style of Brahmi has been changed. The styles of changes of the writing forms are not the same in all places. As a result, the Brahmi alphabet took different shapes in the different regions of India. In course of time, the changing form of the Brahmi alphabet in Bengal had taken the shape of modern Bangla alphabet. Now an attempt may be made to focus the origin and development of the Bangla alphabet by a systematic paleographic study of the early Bengal epigraphic records [26].

1.5 Overview of On-Line Handwriting Recognition

Handwriting is a very personal skill; it consists of graphical marks on a surface and can be used to identify a person. In the process of handwriting, communication is the main purpose, and it achieved by drawing letters or other graphemes. The characters have a certain basic shape, which must be recognizable for a human in order for the communication process to function. There are rules for the combination of letters, if those rules are known to the readers then reader can recognize a character or word. Handwriting was developed as a means of communication and to expand one's own memory. The printing press increased the number of documents available and therefore increased the number of people who learnt to read and write.

Through the increased rate of alphabetization, naturally there was an increased use of handwriting as a means of communication. In various situations, handwriting seems much more practical than typing on a keyboard. For instance, children at school are using notepads and pencils or ink pens, which are regarded as a better tool to teach writing by any teachers. Moreover, according to Plamondon et al., 2000 , “as the length of handwritten messages decreases, the number of people using handwriting increases”. Therefore, it can be concluded that there is little danger of the extinction of handwriting as a communication tool and it is a very important part to improve the literacy level.

1.5.1 On-Line vs. Off-Line Recognition

1.5.1.1 Basic Features of On-Line Recognition

On-line HWR (Hand Writing Recognition) means that the input is converted in real-time, dynamically, while the user is writing. This recognition can lag behind the user's writing speed. (Tappert et al. 1990) report average writing rates of 1.5- 2.5 characters/s for English alphanumerics or 0.2-2.5 characters/s for Chinese characters. In on-line systems, the data usually comes in as a sequence of coordinate points. Essentially, an on-line system accepts as input a stream of x-y coordinates from an input device that captures those data combined with the appropriate measuring times of those points.

1.5.1.2 Basic Features of Off-Line Recognition

Off-line HWR is the application of a HWR algorithm after the writing. It can be performed at any time after the writing has been completed. That includes recognition of data transferred from the real-ink pens to a computing device after the writing has been completed. The standard case of off-line HWR, however, is a subset of optical character recognition (OCR). A scanner transfers the physical image on paper into a bitmap, the character recognition is performed on the bitmap. An OCR system can recognize several hundred characters per second. Images are usually binarised by a threshold of its color pattern, such that the image pixels are either 1 or 0 (Santosh et. al. 2009).

1.5.1.3 Similarities and Differences between On-Line and Off-Line Recognition

There are two main differences between on-line and off-line handwriting recognition. Firstly, off-line recognition is executed after the time of writing.

Therefore, a complete piece of writing can be expected as an input by the machine. Secondly, on-line devices also get the dynamic information of the writing as input, since each point coordinate is captured at a specific point of time, which can be provided to the handwriting recognizer along with the point coordinates by the operating system. In addition, the recognizer has information about the input stroke sequence, the stroke direction and the speed of the writing. In the off-line case these pieces of information are not readily available, but can be partially reconstructed from the off-line data (Santosh et. al. 2009).

All these information can be an advantage for an on-line system, however, off-line systems have used algorithms of line-thinning, such that the data consists of point coordinates, similar to the input of on-line systems (Tappert et al. 1990). When line thinning has been applied, an off-line system could estimate the trajectory of the writing and then use the same algorithm as an on-line system. Vice versa, an on-line system can employ algorithms of off-line systems, since it is possible to construct a binary image from mouse coordinates of points. However, only few systems of that kind have been developed.

1.6 Overview of E-Learning and Autonomous Learning

The term e-learning refers to a number of different methods, concepts and techniques. In literature, there are different definitions of what e-learning is and what it is supposed to be (Rosenberg et. al. 2006) defines e-learning as follows:

E-learning is the use of Internet technologies to create and deliver a rich learning environment that includes a broad array of instruction and information resources and solutions, the goal of which is to enhance individual and organizational performance.

It can be noted that (Rosenberg et. al. 2006) defines e-learning purely by terms of instruction and information resources. Further, the use of Internet technologies is seen as a necessary condition for e-learning. The definition does not take into account educational software. Seel and Ifenthaler (2009) claim that the terms e-learning and learning on-line are synonymous. (Richert et. al. 2007) criticizes the definition of Rosenberg because she sees no reason for such equality of terms. She constitutes her view with the fact that electronic (learning) applications are not limited to the Internet.

Richert et. al. 2007 defines e-learning as:

E-learning is defined as computer-aided learning (mainly by individuals) with hypertext and multimedia based interactive systems. The learning process can take place independent of time and location both on-line and offline.

It is important to note that the term is broader than the definition of Rosenberg, but is restricted to learning systems. That means concretely that electronic media like dictionaries may be included in e-learning systems as a tool, however, they can only form a part of a more

1.6.1 Classification of E-Learning Systems

E-learning systems can be classified by their their degree of freedom for user interaction. On one end of the scale there are Drill-and-Practise programs that do not allow for freedom of interaction. On the other end there are interactive programs allowing the user to interact and control the application. Judged by the definition of Richert this classification does not seem very suitable (Richert 2007).

Another possibility to classify e-learning systems is the the kind of storage media used. This classification allows for a distinction between on-line and offline e-learning systems. Offline systems are those systems that are offered on passive storage media like floppy disk, CD-ROM. Offline systems are usually called Computer Based Training (CBT) systems. On-line systems on the other hand are web server based systems that fall under the category of Web Based Training (WBT) systems (Richert et. al. 2007).

Additionally, Richert (2007) defines hybrid systems that are CBT systems but use the Internet as a means of communication with other learners. Table 1.2 shows the classification of e-learning systems (Richert et. al. 2007).

Table 1.2: Classification of e-learning systems

		Using the WWW for storage	
		Yes	No
Using the WWW for communication	No	WBT	CBT
	Yes	Learning platforms	Hybrid CBT

1.6.2 Pedagogical Context of E-Learning

The pedagogical context of e-learning is a crucial part of any e-learning environment. The learning targets need to be defined and a conceptual design of software needs to be based on learning targets necessity.

1.6.2.1 Learning

The term learning has a very complex nature. A definition of learning is therefore never sharply confined. The definition of learning by Lefrancois et. al. 1994 shows how broad the term can be perceived.

In German:
Lernen umfasst alle Verhaltensänderungen, die aufgrund von Erfahrungen zustandekommen.

In English: Learning compasses all changes in behaviour that are based on experience.

The changes in behaviour include those processes that do not aim at acquiring information, but also those changes in behaviour of an unknown cause (Lefrancois et. al. 1994). According to (Richert et. al. 2007), this means the acquisition of competences of different kinds.

1.6.2.2 Intelligent Tutorial Systems

Intelligent tutorial systems fall under the paradigm of cognitive learning. The general scheme of such a system is depicted after (Richert et. al. 2007). The declarative knowledge of a system is stored in the expert module. The student module holds information about the learning progress and the course module holds the lessons of the application. The communication module interacts with the learner. A problem of these systems is that they cannot distinguish between small oversights and serious

2 BENGALI HANDWRITING EDUCATION SYSTEM DESIGN AND IMPLEMENTATION

As we described in chapter 1.1, the objectives of our study is to design and development of web-based (iPhone/smartphone or computer browser) intelligent handwriting education system for autonomous learning of Bengali characters. Thus, the students, especially children or older people, who do not have chance to go to school, can practice their handwriting at anywhere at any time. So that 100% literacy improvement can be established within a very short period in Bangladesh. In this chapter, we will describe about the detail of design and implementation of Bengali handwriting education system.

2.1 Learning System Architecture

Figure 2.1 represents the operational flow of our proposed Bengali handwriting education system for autonomous learning. The proposed system is composed of two modules: the guided writing mode and the free writing one. The architecture of the system is detailed in Figure 2.2. As shown in Figure 2.2 (a), students have the choice to practice the guided handwriting mode or the free one. In case of free handwriting mode, writing will be done on a blank area, Figure 2.2(b). The guided writing mode is one of the beginning level of education designed for the children's who are in the early stages of learning. This tool displays a transparent image onto the digital web interface comprising this handwriting template, Figure 2.2(a). The student is then invited to follow this image to replicate the pattern of Bengali character.

After student submits their sample character, handwriting input was received in our recognition server (saying as virtual teacher) through WWW client-server interface. Then, by matching the handwriting template and the handwriting input, the recognition of the inputted character will be carried out. Finally, the automatic stroke error detection engine can immediately locate the student's handwriting errors and provide an immediate feedback to the student about the location of the error; their type and how to correct them (Table 2.4 and Table 2.5). The details of the automatic stroke error detection and hierarchical recognition methodology will be described in the following sections.

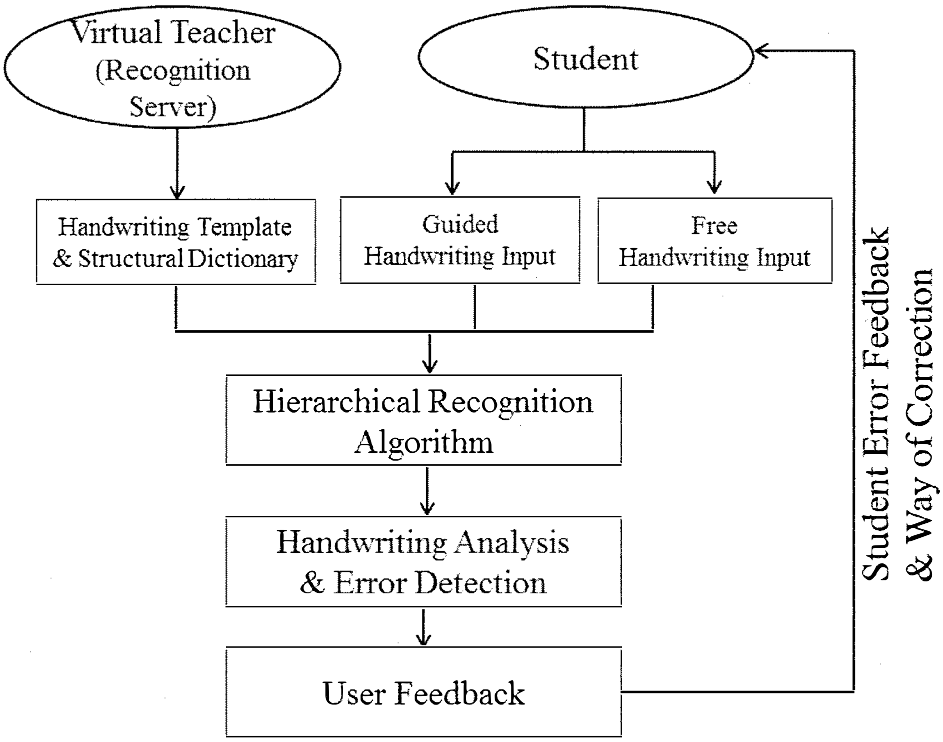


Figure 2.1: The architecture of the proposed Bengali handwriting education system

We have developed a digital web interface that can access from both of smartphone or computer browser. Figure 2.2 shows the snapshot of our web-based digital interface. It has three fields: (1) Handwriting character input field, (2) Recognized character output field, and (3) Options buttons field. While the users write Bengali characters with an input device (e.g., pen, mouse, finger etc.) on the character input field. Then, our digital web interface gets the corresponding stroke data (sequence of points) and sent to recognition server. Those data stored at the database, later we used it to evaluate our proposed education system. Once the interface gets the recognition result from the server, result is displayed at the character output field with system font including student's error feedback.

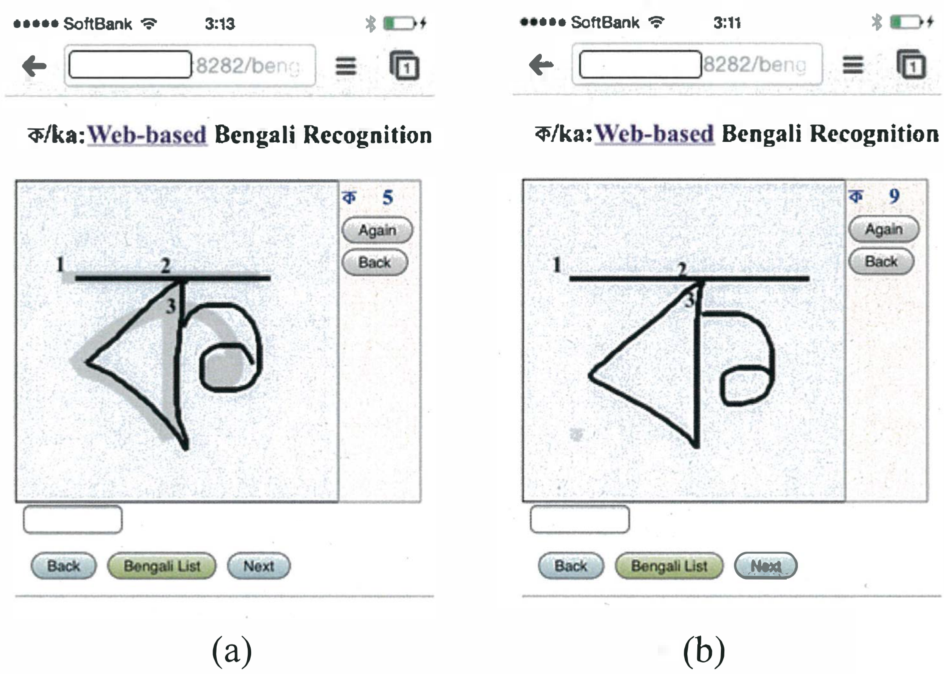


Figure 2.2: Digital web interface for Bengali handwriting education system that can be accessed from both of iPhone/smartphone or computer browser: (a) Guided handwriting mode (b) Free handwriting mode

2.2 *Character Recognition Methodology*

2.2.1 *Web-Based (Client-Server) Recognition Architecture*

In our bengali handwriting education system, a web-based handwriting client-server interface technique has been used for character recognition and student's feedback. We have designed the proposed system with the following distinctive features: (1) it is a web-based system developed by Java web application technology and works on WWW client browser (iPhone/smartphone or computer browser), (2) easy character input environment is provided according to use of rich editing functions and the input device (e.g., pen, mouse, finger etc.), (3) HTML5 canvas technology was used to detect and draw student input, (4) Apache Tomcat web server and PostgreSQL database were used for system implementation, (5) consecutive handwriting and recognition is possible, and (6) immediate student feedback.

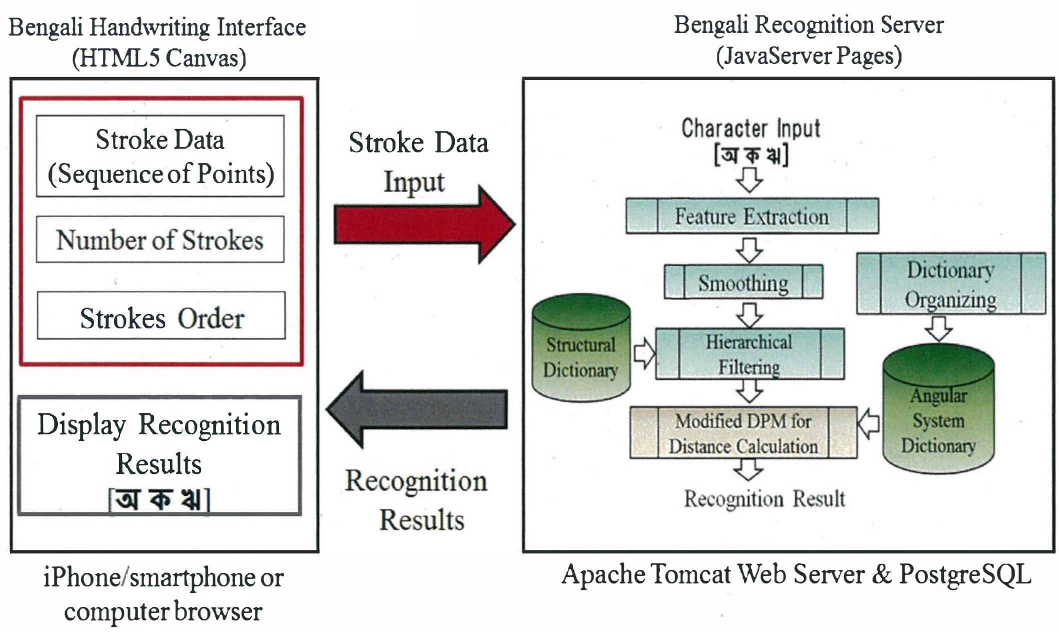
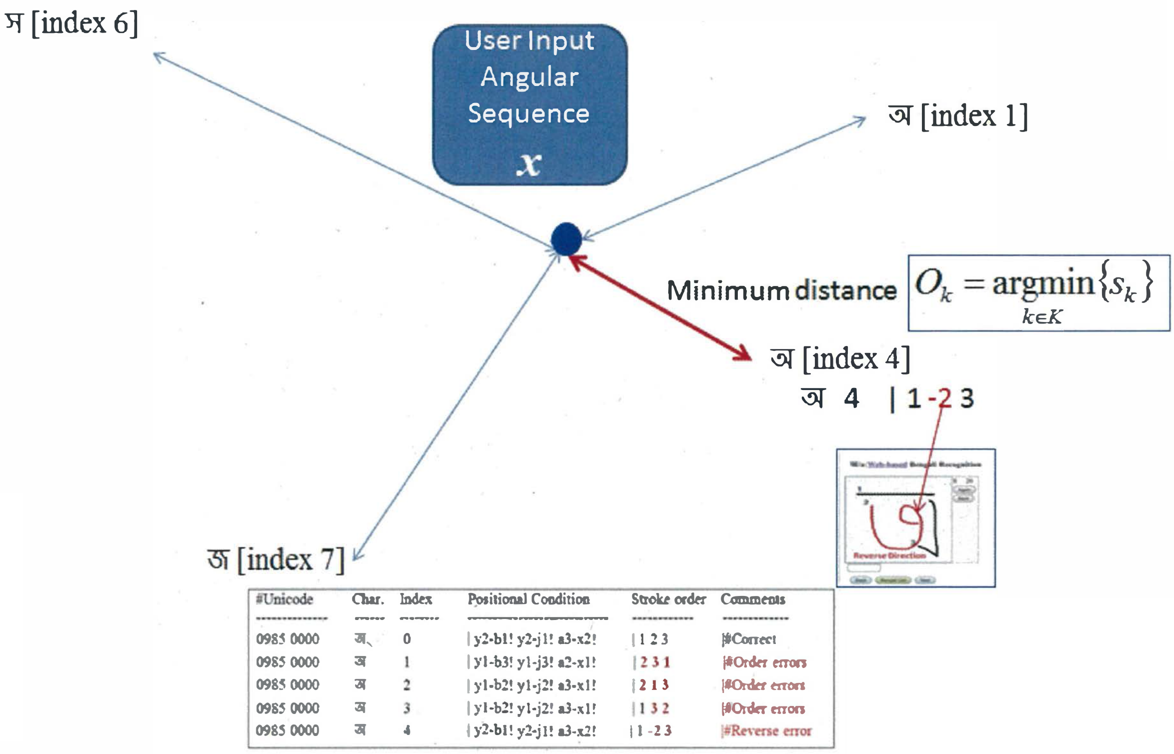


Figure 2.3: Handwriting recognition architecture for web-based Bengali handwritten education system

Figure 2.3 shows the handwriting recognition architecture that contains both of web-based handwriting interface and character recognition servers. Handwriting interface program is generated by Java Server Pages (JSP) and runs on WWW client, such as computer browser or smartphone browser. On the other hand, JSP based character recognition engine works on Apache Tomcat web server. While the students write Bengali characters with an input device (e.g., pen, mouse, finger etc.) on the character input field. Then, our digital web interface gets the corresponding stroke data as (x, y) coordinates and sent to the character recognition server. After that, the recognition engine converts the student's stroke data into angular feature in feature extraction stage, see in left side of Figure 2.5. After applying smoothing (Figure 2.6) to those extracted angular feature, our algorithm entered into hierarchical filtering stage. In this stage, we have applied a series of filters in a hierarchical manner to reduce the search space of final DPM. The first filter performs coarse classification on a large number of candidates based on the high-level features of stroke patterns, such as stroke number. It reduces the candidate character models. Then the second filter performs structural preselection among the resulted samples of filter 1, based on the structural information of Bengali characters stored in our predefined structural dictionary (Table 2.3). As shown in Figure 2.4, our algorithm calculates the structural distance between input character and each of stored structural patterns in filter 2. Then the index number of structural patterns with minimum structural distance is selected as filter 2 resulted characters. Thus, our recognition engine can identify the stroke error patterns from the structural information of corresponding index number stored in our predefined structural dictionary (Table 2.3). The detail of stroke error detection will be discussed in following section. Again, it reduces to a small number of candidates for final DPM. In the final matching stage, low-level features (angular feature) are used to guide a DPM algorithm. In this stage, it calculates distance between input strokes and template strokes of each preselected characters by using our modified DPM. The character with Minimum distance is selected as recognition result (See in Figure 2.4). Finally, our recognition engine returns k top ranked characters as recognition results to client side browser. Then, it displayed the results into recognized character output field of our digital web interface.



#Unicode	Char.	Index	Positional Condition	Stroke order	Comments
0985 0000	অ	0	| y2-b1! y2-j1! a3-x2!	| 1 2 3	|#Correct
0985 0000	অ	1	| y1-b3! y1-j3! a2-x1!	| 2 3 1	|#Order errors
0985 0000	অ	2	| y1-b2! y1-j2! a3-x1!	| 2 1 3	|#Order errors
0985 0000	অ	3	| y1-b2! y1-j2! a3-x1!	| 1 3 2	|#Order errors
0985 0000	অ	4	| y2-b1! y2-j1! a3-x2!	| 1 -2 3	|#Reverse error

Figure 2.4: The working mechanism of handwriting recognition algorithm to recognize the user's input character together with their stroke error detection.

2.2.2 *Feature Extraction*

In our online handwriting recognition engine, we used client-server interface to extract the feature points and relevant structural information as (x, y) coordinates along the trajectory of the input devices (e.g., pen, mouse, finger etc.) onto the digital web interface for each strokes separately. Then, we convert it to the angular feature points for every stroke and stored into different arrays of corresponding stroke. Figure 2.5 shows an easy example of angular conversion for the one stroke Bengali character "২". Here, we used the angular conversion range from -180° to 180° as shown in Figure 2.5 (right side).

Equation 1 represents the conversion formula, where x_i, x_{i-1} represent the x coordinates of two consecutive points, y_i, y_{i-1} represent the y coordinates of two consecutive points and the length of x, y coordinates is $(I+1)$. The number of points is proportional to the stroke's length of handwriting characters.

$$\theta_i = \frac{180}{\pi} \times \tan^{-1} \frac{y_i - y_{i-1}}{x_i - x_{i-1}} \qquad (1 \le i \le I) \qquad (1)$$

If the written stroke's length is long, then the number of feature points will be large and vice versa. Figure 2.5 shows an easy example, so the number of points will be small, but in actual handwriting case, the number of feature points will be large. Moreover, slow handwriting results large number of feature points and fast handwriting gives the small number of feature points. In our system, angular feature of original template characters is stored into an array ***t***. After the detection of reverse stroke direction, our algorithm automatically converted angular feature of original template characters and stored into an array ***r***.

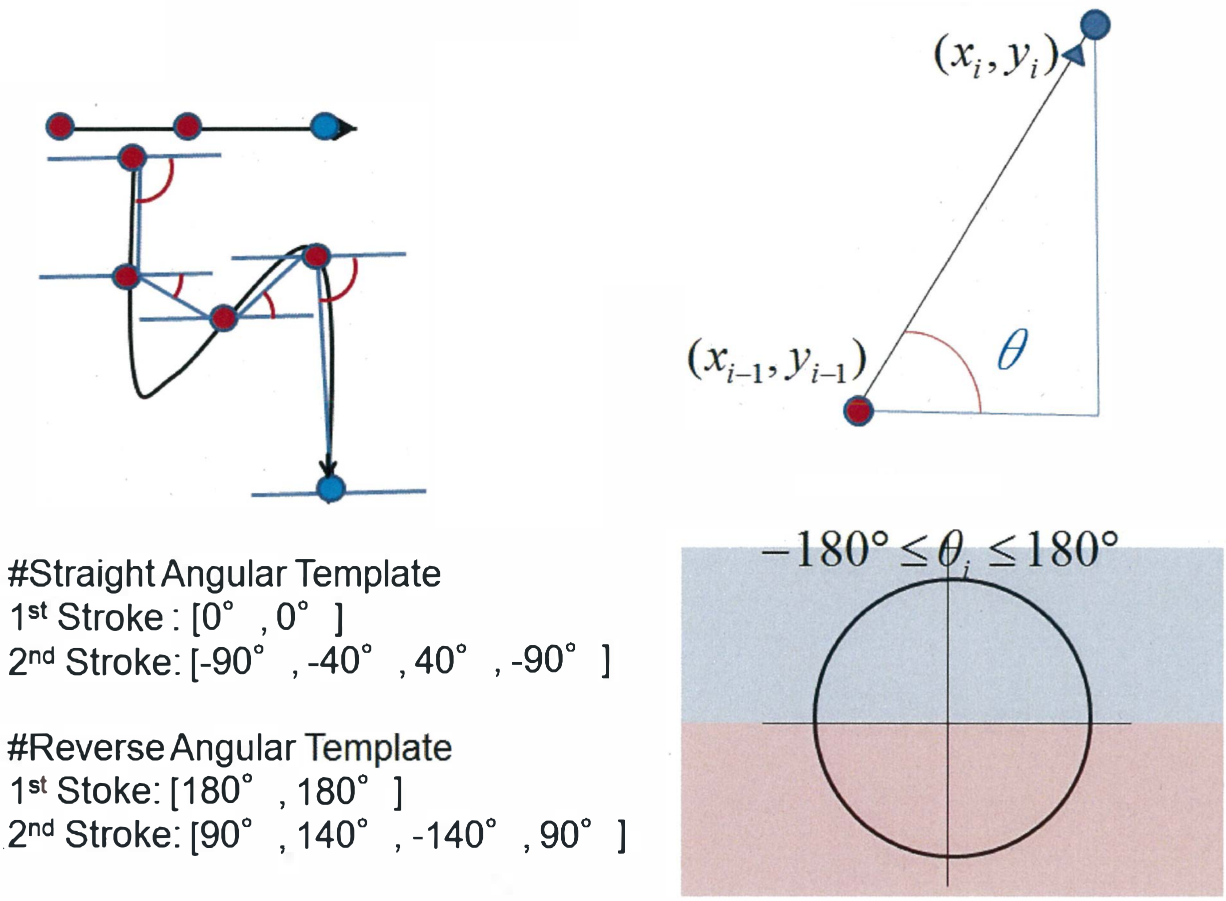


Figure 2.5: Example of angular conversion for the Bengali character “দ(da)”.

2.2.3 Smoothing

As we described in above section, our proposed recognition engine extracts the feature points along the trajectory of the input devices (e.g., pen, mouse, finger etc.) onto the digital web interface. But, the stroke drawn on digital web interface with a pen, mouse or finger input contains noise. Because, digitizing errors like limited accuracy of the tablet or erratic pen-down indication or hand fluctuation cause noises in the input data. Since the prototype is a learning application and not pure handwriting recognition, the main issue seems the size of the character. The normalization is done by applying the 5 point median smoothing technique to eliminate the noise from the angular feature data. In order not to lose any data, the complete list of points is maintained, there is no point reduction, and it remains the original angular value.

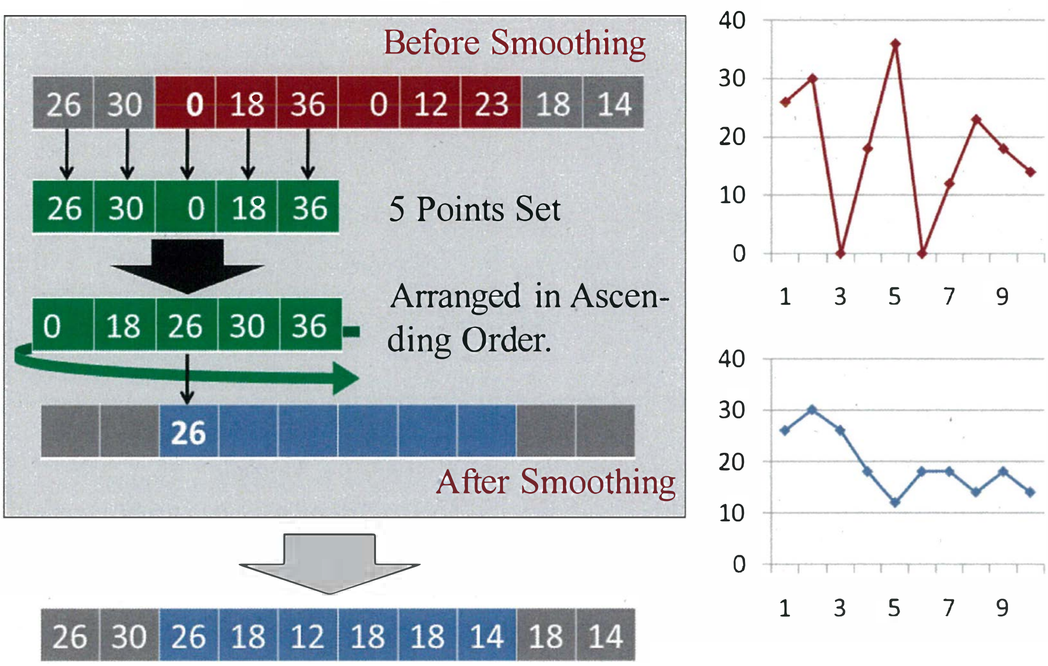


Figure 2.6: The procedures of 5- point median smoothing technique to eliminate the noise from the angular feature data by considering before and after the smoothen data.

Figure 2.6 shows the basic procedures of 5-point smoothing technique considering before and after the smoothen data. In this smoothing technique, our algorithm selects the 5 points starting from a certain position, and arranges all these 5 points in ascending order. Then, it selects the middle value of 5 points, and put in that certain position. The same procedures recursively applied for all of angular feature data. Thus, there is no data loss occurred. In the following figure, the two angular data at both ends do not have surrounding 5 points data, so it remains unchanged. The right side of Figure 2.6 shows the graph of angular data before and after smoothing.

2.2.4 *The Flow of Hierarchical Recognition System*

This research project was aiming to develop a web-based (iPhone/smartphone or computer browser) Bengali education system. We need an efficient recognition algorithm that gives higher accuracy with improved recognition speed. To speed up our recognition system, a series of filters have been applied in a hierarchical manner before applying into the final matching algorithm. It reduces the recognition search space and speed up our Bengali education system. Figure 2.7 shows the hierarchical recognition flow of our proposed system. The first filter performs coarse classification on a large number of candidates based on the high level features of stroke patterns, e.g., number of strokes, to reduce candidate character models. Then the second filter performs structural preselection based on the structural information of Bengali characters stored in our predefined structural dictionary, we named it as Bengali Structural Dictionary. It reduced to a small number of candidates for final Dynamic Programming Matching (DPM).

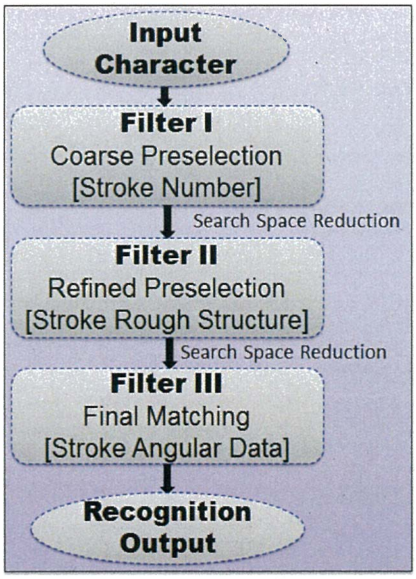


Figure 2.7: Operational flow of hierarchical recognition architecture for web-based Bengali handwriting education system

In the final matching, low-level features (angular feature) are used to guide DPM classification. The resulting *k* top ranked candidates are sent as recognition results. In this way, the proposed hierarchy can largely save the DPM calculation time, thus recognition speed and accuracy has improved that makes our system adaptable for real-time web-based Bengali education sytem.

Filter I: Coarse Preselection Based on Stroke Numbers

Bengali is a multi-stroke input characters with extremely long cursive shaped where it has stroke order variability and stroke direction variability. Bengali charcter can be categorized based on its stroke numbers (high-level feature) as shown in Table 2.1. Coarse preselection using this high-level feature (stroke numbers) among the large number of candidate characters, can reduce the recognition search space into five different levels, from 50 to 7, 20, 19, 3 and 1. In our hierarchical recognition architecture, Filter I performed coarse classification on a large number of candidates based on the stroke numbers and thus improved the recognition speed.

Table 2.1: Different categories of Bengali characters based on its stroke numbers

Level	**Number of Strokes**	**Bengali Characters**	**Number of Characters**
1	1	এ ও ৎ খ থ গ ঙ	7
2	2	ঋ ঔ ঘ য ম ঝ ঠ চ ঢ ত দ ফ ব ড ভ ল হ ং ঃ ঁ	20
3	3	অ ই ঈ উ ঐ ক ছ জ ঞ ট ঢ় র শ ণ ন ষ য় স ড়	19
4	4	ঊ ধ প	3
5	5	আ	1

Filter II: Refined Preselection Based on Bengali Character's Structural Patterns

Filter II is applied on the resulted candidates of Filter I for the further reduction of recognition search space that helps to speed up our web-based education system. In this stage, a hierarchical structured dictionary was used to perform structural preselection. It contained structural information of Bengali characters, e.g., stroke position, stroke combination, stroke crossing or not crossing etc. Figure 2.8 shows an example of structural difference between the Bengali characters "ন (na)" and "ম (ma)". Both of these two characters have two numbers of strokes and belong to the same level 2 in Filter I preselection (Table 2.1). In our hierarchical recognition engine, Filter II is applied to classify between these two characters based on their structural patterns as shown in Figure 2.8, the second stroke's starting and ending points of "ন (na)" and "ম (ma)" are opposite from each other. We used this structural information to classify between these two characters using our predefined structural dictionary (Table 2.3).

Table 2.2 represents the symbolic notation of Bengali character stroke's position. We have used this notation to edit our predefined structural dictionary. Here, the co-ordinate for starting and ending point of 1^{st} stroke represented as (x1, y1) and (i1, j1) respectively. Center point of 1^{st} stroke was represented as (a1, b1) and calculated from (x1, y1) and (i1, j1). Here, the numbers of co-ordinate data are followed by the stroke number of any Bengali characters.

Table 2.2: The symbolic notation of Bengali character stroke's position using (x, y) co-ordinates

#	**Stroke position**	**Stroke's X-Axis Notation for 1st stroke**	**Stroke's Y-Axis Notation for 1st stroke**
1	Starting Point	x1	y1
2	Center Point	a1=(x1+i1)/2	b1=(y1+j1)/2
3	Ending Point	i1	j1

In Figure 2.8, the x-axis data of 2nd stroke's starting and ending points for "ন (na)" and "ম (ma)" can be represented as x2 and i2 respectively. The second stroke's starting and ending points for Bengali characters "ন (na)" and "ম (ma)" are opposite from each other. In case of "ন (na)", x2 is greater than i2 and it can be represented as x2-i2! (x2-i2>=0) in our predefined structural dictionary (Table 2.3). Oppositely, i2 is greater than x2 for Bengali character "ম (ma)" and it can be represented as i2- x2! (i2- x2>=0) in our structural dictionary.

Table 2.3 represents the examples of our structural dictionary for Bengali character "ন (na)" and "ম (ma)". Here, (x, y) and (i, j) with corresponding stroke number represents the starting and ending point of input stroke respectively. (a, b) is the central point and calculated as a=(x+i)/2; b=(y+j)/2. For example, (x1, y1), (i1, j1) and (a1, b1) represents the starting, ending and central point of 1st stroke. Similarly, the (x2, y2), (i2, j2), (a2, b2) represent the starting, ending and central point of 2nd stroke.

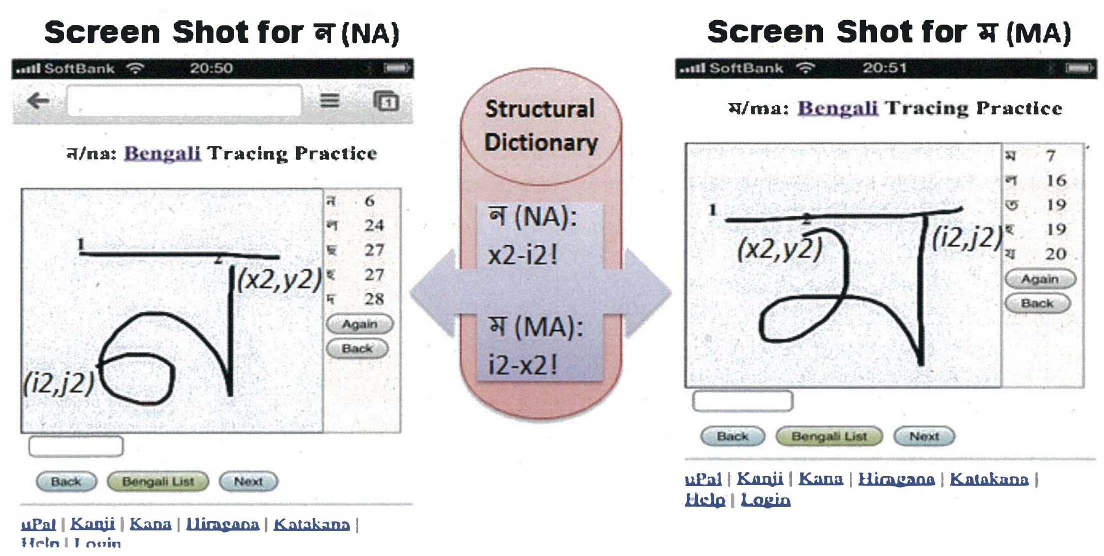


Figure 2.8: An example of structural difference between Bengali characters "ন (na)" and "ম (ma)"

In this structural dictionary, single template character was presented with multiple structural patterns depend on its probable handwriting errors [David et al., 1997]. For example, the Bengali character "ন (na)" and "ম (ma)" has 6 different structural patterns considering its probable error case. Here, the 3rd column, index is used to identify the handwriting error pattern of corresponding student's input. The 4th column, positional condition is used to locate stroke relationship error and provide correct recognition output together with necessary error feedback. The 5th column, stroke pattern is used to identify which stroke sequence was inputted and then provides colorful feedback to students about their handwriting stroke sequence. Also, it identifies the reverse stroke direction errors by checking the negative value in stroke pattern column (5th column in Table 2.3). The all of this error detection mechanism will be discussed detail in section "2.3 Automatic stroke error detection and stroke feedback".

Table 2.3: Examples of predefined structural dictionary for the Bengali character "ন (na)" and "ম (ma)"

#Unicode	Char.	Index	Positional Condition	Stroke Pattern	Comments
09A8 0000	ন	0	| b2-b1! x2-i2!	| 1 2	|#Black for all: Correct
09A8 0000	ন	1	| b2-b1! i2-x2!	| 1 -2	|#Red for 2nd : Direction
09A8 0000	ন	2	| b2-b1! x2-i2!	| -1 -2	|#Red for all: Direction error
09A8 0000	ন	3	| b1-b2! x1-i1!	| 2 1	|#Brown for all: Order error
09A8 0000	ন	4	| b2-b1! x2-i2!	| -2 1	|#Red for 1st :Direction error
09A8 0000	ন	5	| b1-b2! i1-x1!	| -2 -1	|#Red for all: Direction error
:	:	:	:	:	:
09AE 0000	ম	0	| b2-b1! i2-x2!	| 1 2	|#Black for all: Correct
09AE 0000	ম	1	| b2-b1! x2-i2!	| 1 -2	|#Red for 2nd : Direction
09AE 0000	ম	2	| b2-b1! i2-x2!	| -1 -2	|#Red for all: Direction error
09AE 0000	ম	3	| b1-b2! i1-x1!	| 2 1	|#Brown for all: Order error
09AE 0000	ম	4	| b2-b1! i2-x2!	| -2 1	|#Red for 1st : Direction error
09AE 0000	ম	5	| b2-b1! x2-i2!	| -2 -1	|#Red for all: Direction error

In our Bengali education system, recognition engine read the classification rule from predefined structural dictionary and applied those rules to classify between resulted candidates of Filter I. By using this classification rule, Filter II can successfully preselect the desired candidate characters for the final DPM matching. Thus, it further reduced the recognition search space and speed up our recognition engine to adapt with web-based Bengali education system.

Filter III: Final Matching by DPM with Writing Speed-free Recognition Technique

In this section, we explained about our proposed modified dynamic programming matching algorithm that support writing speed free recognition. In our proposed system, the recognition scheme is carried out using dynamic programming concept which is modified by accepting different length of input feature points to support writing speed free recognition. According to DPM algorithm, handwritten input pattern is matched with template patterns by calculating optimal matching cost, also known as character distance (Hu et al., 2007; Joshi et al., 2006; Prasanth et al., 2007; Tan et al., 2002; Shin et al., 2004; Tonouchi et al., 1997). In our recognition scheme, the term character distance stands for the angular difference between input stroke's angles and corresponding template stroke's angles. Then the character with optimal distance is selected as our recognition output and return back to students with necessary feedback. The mathematical notation for DPM is explained as follows.

To match handwritten input character with the template characters, we calculate character distance, D_k for corresponding template pattern k. A distance D_k for the candidate character k can be calculated as follows,

$$D_k = \frac{1}{L}\sum_{l=1}^{L} d_{kl} \tag{2}$$

Where, L is the number of total input strokes (e.g., in case of Bengali character অ(a), the number of input strokes $L=3$), and k is the number of candidate template characters, and l is the number of handwritten strokes. The candidate character with smallest D_k is selected as the recognition result for current handwritten input character. The stroke distance for each template character can be calculated using dynamic programming matching technique as follows,

$$d_{kl} = \frac{g(I_l, J_{kl})}{I_l + J_{kl}} \tag{3}$$

Where, $g(I_l\ ,\ J_{kl})$ represents the modified DPM distance between input feature vector length I_l and k_{th} template feature vector length J_{kl} for corresponding stroke l. We have modified the recurrence relation of DPM algorithm as below to find the character distance between two stroke sequences,

Initially,

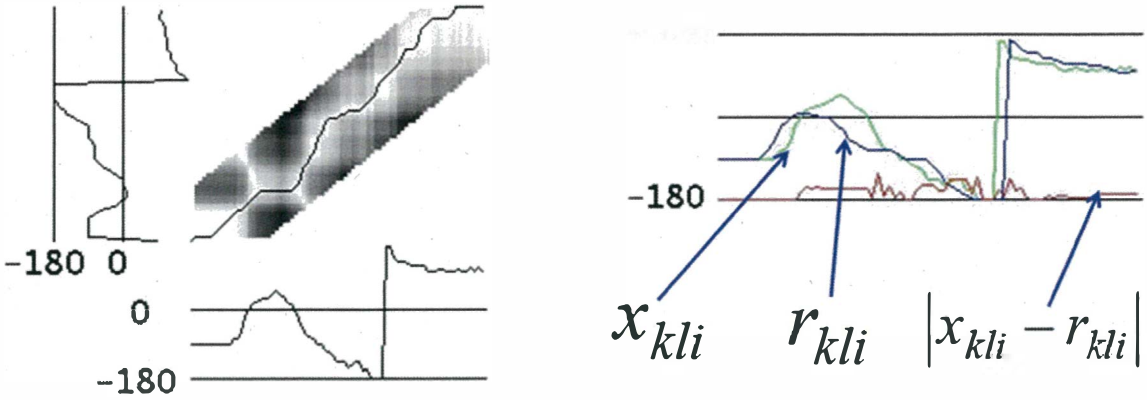
$$g(i_l, j_{kl}) = \begin{cases} 0 & (i = 0, j_{kl} = 0) \\ \infty & (\text{other}) \end{cases} \tag{4}$$

Recursively,

$$g(i_l, j_{kl}) = \min \begin{cases} g(i_l - 2, j_{kl} - 1) + 2d(i_l - 1, j_{kl}) + d(i_l, j_{kl}) \\ g(i_l - 1, j_{kl} - 1) + 2d(i_l, j_{kl}) \\ g(i_l - 1, j_{kl} - 2) + 2d(i_l, j_{kl} - 1) + d(i_l, j_{kl}) \end{cases} \tag{5}$$

$$1 \le i \le I_l, \max\{1, i \times {}^{J_{kl}}\!/\!_{I_l} - W\} \le j_{kl} \le \min\{J_{kl}, i \times {}^{J_{kl}}\!/\!_{I_l} - W\}$$

Where, $g(i_l,\ j_{kl})$ is the cumulative distance up to the current template character, $d(i_l, j_{kl})$ is local cost for measuring the dissimilarity between i_l^{th} and j_{kl}^{th} point of two sequences.



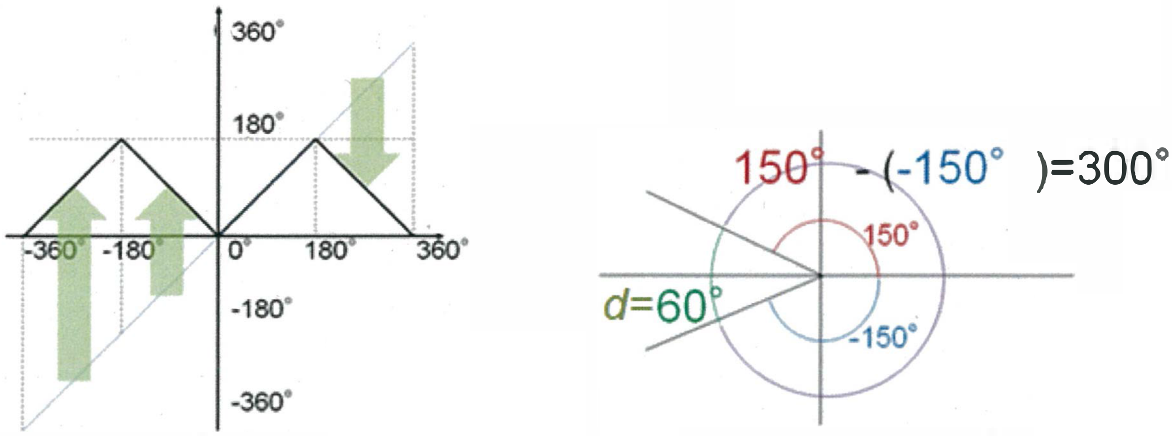
(a) (b)

Figure 2.9: Dynamic programming matching: (a) illustration of wrapping path for Bengali character ড(da) (b) Calculation of local distance also known as dissimilarity between two strokes sequences.

Figure 2.9 represents illustration of wrapping path for DP matching and dissimilarity measurement between two strokes sequence. Here, x_{kli} represents the student's input stroke angles and r_{kli} represents the template stroke angles. We assumed that x_{il} represents the angular sequence of l^{th} input stroke and r_{klj} represents angular sequence of l^{th} template stroke of k^{th} character. The local distance as well as dissimilarity between the two stroke sequences can be measured as below:

$$d(i_l, \cdot\ ) - \begin{cases} |x_{il} - r_{klj}| & (-180^\circ \le |x_{il} - r_{klj}| \le 180^\circ) \\ {}^{\circ} - |\ _{il} - r_{k}\ | & (|x_{il} - r_{klj}| < -180^\circ) \text{ or } (180^\circ < |x_{il} - r_{klj}|) \end{cases}$$

(6)



(a) (b)

Figure 2.10: (a) Angular conversion process considering the angular distance range of 0°~ 180°. (b) Example of the difference by the angular distance range 0°~ 180°.

The difference of two angular features takes the range of -360° degree~360°. However, the angular range of 0°~ 180° is effective for the calculation. For this reason, we considered the angular distance range of 0°~ 180° for ease of calculation. Figure 2.10 represents the angular conversion process considering the angular distance range of 0°~ 180°. For example, as shown in Figure 2.10 (b), although the angular difference between 150° and -150° will be 300 degrees, we considered angular distance as 60° in our recognition algorithm.

To establish writing speed free recognition, we modified the traditional dynamic programming matching algorithm. As we explained in previous section, our handwriting digital web interface extracts the user stroke data (feature points) and sent to our recognition server. Fundamentally, the number of extracted feature points is inversely proportional to student's handwriting speed. Slow writing speed provides large number of feature points, and oppositely fast writing has small number of feature points. Local cost as well as dissimilarity measurement between i_l^{th} and j_{kl}^{th} point of two sequences can be calculated by $d(i_l, j_{kl})$ where i_l is the number of angular feature points of l^{th} input stroke and j_{kl} is the number of angular feature points of l^{th} stroke of k^{th} template character. For slow handwriting case, i_l may greater than or equal to $2*j_{kl}$. Oppositely in case of fast handwriting, j_{kl} may greater than or equal to $2*\ i_l$. In this condition, the calculation of local stroke distance, dissimilarity measurement $d(i_l,\ j_{kl})$ (in equation 4) may fail due to the adaptability problem of adjustment window size in DPM algorithm. To avoid this problem, we modified the existing DPM to accept the input strokes data of any length wherever it greater or smaller than two times of corresponding template stroke's length.

For instance, we considered a slow handwriting case of children or older people where the number of angular data of input stroke i_l may greater than or equal to $2*j_{kl}$, the number of angular data for l^{th} stroke of k^{th} template character. We assume i_l is 24 and j_{kl} is 9. In this case, our modified DPM only consider the even sequences of angular data for input stroke i_l . In this way, modified DPM can successfully solved the adaptability problem of dissimilarity measurement $d(i_l, j_{kl})$ (in equation 4). Thus, our proposed Bengali education system can accept both of fast and slow handwriting of children and older people.

In addition, we modified the following settings of adaptive adjustment window size as equation 7 to accept any pattern of handwriting input. Here, W represents the adjustment window size. From the experimental analysis, we found the optimal value of $W=18$, that makes our system highly adaptable to recognize rough handwriting characters. Here I_l represents the total number of input stroke sequence and J_{kl} represents the total number of template stroke sequences of corresponding stroke l.

$$1 \le i \le I_l, \max\{1, i \times {}^{J_{kl}}\!/\!_{I_l} - W\} \le j_{kl} \le \min\{J_{kl}, i \times {}^{J_{kl}}\!/\!_{I_l} - W\} \tag{7}$$

In practical, our intelligent Bengali handwriting education system was developed to improve the Bengali literacy rate by considering both of children and older students. Basically, children have slow handwriting speed and aged people have fast handwriting speed. By the above modification, our recognition engine can accept both of input patterns from children and older people. In this way, we can successfully implement the writers' independent recognition algorithm for our web-based Bengali handwriting education system. By using this writing speed free recognition technique, the accuracy was improved considerably. In a later section, we evaluate our proposed system using a rich Bengali handwritten character database

2.3 Automatic Stroke Error Detection & Stroke Feedback

2.3.1 Student Feedback for Autonomous Learning

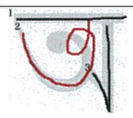
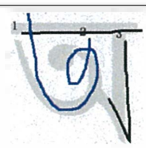
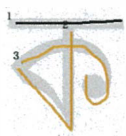
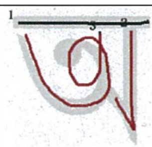
In our Bengali handwriting education system, we have developed an automatic stroke error detection methodology. It aims to identify the handwriting errors in student's handwriting and provide immediate feedback. We classified the handwriting errors as stroke production error and stroke relationship error and stroke order error. Stroke production error consists of reverse stroke direction, split stroke and merge stroke errors etc.

On the other hand, stroke relationship error is the error where students write the stroke with extra length and the stroke order error is the error of wrong stroke sequence. Our automatic stroke error detection engine identifies the student's handwriting error and provides feedback to correct them. This error detection methodology was implemented using JSON: JavaScript Object Notation technology, see in Figure 2.11.

Table 2.4: Bengali handwriting error and idea of student's error feedback

#	Error Category	Error Details	Color Marked Feedback
a	Correct handwriting	Correct Stroke	**Black**
b	Stroke production errors	Reverse direction	**Red**
		Split/broken stroke	**Purple**
c	Stroke relationship error	Stroke with extra length	**Blue**
d	Stroke order error	Wrong Stroke Sequence	**Brown**

Table 2.5: Examples of handwriting error patterns of Bengali characters: (1, 2) Stroke production error. (3) Stroke relationship error. (4) Stroke order error. (Numeric symbols means stroke no. and its start point)

#	Student's Error Feedback	Error Type	#	Student's Error Feedback	Error Type
1		Reverse stroke direction (**Red**)	3		Stroke with extra length (**Blue**)
2		Split stroke (**Purple**)	4		Wrong stroke order (**Brown**)

In this methodology, we marked erroneous strokes using different color models depend on the student's handwriting errors as shown in Table 2.4 and Table 2.5. The notation of "{"r":["অ", "score"], "d":[1,-2,3], "c":["**black**","**red**","**black**"]}" is an example to clarify our proposed JSON technique. Here, we marked the reverse direction input stroke for character অ[a] by the red color. In this notation, "r" stands for the recognized character and its recognition score, "d" represents the stroke orders, and "c" is the color combination to mark the reversely inputted stroke. While the students write any stroke with reverse direction then our system detect it and feedback with appropriate color marking. In this case, the second stroke was marked as red color. Thus, our proposed education system feedback student's error using different color models depend on their handwriting errors as shown in Table 2.4 and 2.5.

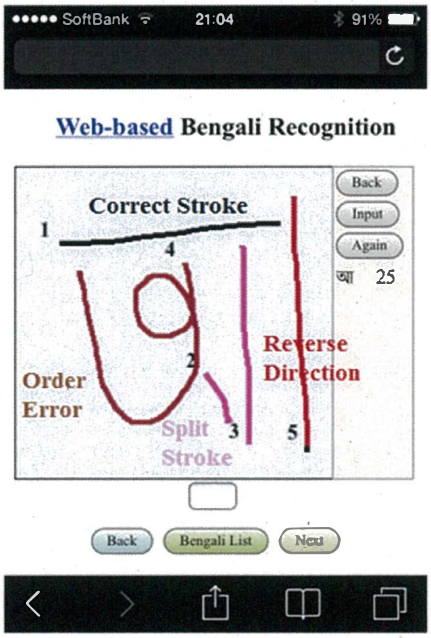


Figure 2.11: Automatic error detection and colorful feedback to correct student's erroneous handwriting (Numeric symbols means stroke number and its starting point)

Figure 2.11 represents the snapshot of student's feedback result to correct their error handwriting. Our proposed education systems can successfully feedback to the students about their error handwriting using colorful marking technology. We implemented this method to our system by JSON technology.

2.3.2 Automatic Stroke Error Detection: How Does It Work

In our web-based intelligent handwriting education system, we developed predefined structural dictionary based on the structural information of Bengali characters. Table 2.3 is the examples of structural dictionary for a single Bengali characters "ন (na)" and "ম (ma)". Based on this information, our recognition engine can successfully recognize the handwriting errors of Bengali characters and then feedback to students with necessary color marking.

As we described in Table 2.3, the single character pattern was presented with multiple structural patterns depend on its probable handwriting errors in our designed structural dictionary [David et al., 1997]. For example, the Bengali character "ন (na)" and "ম (ma)" has 12 different structural patterns considering its probable error case. Here, the third column, index is used to identify the handwriting error pattern of corresponding student's input. The fourth column, positional condition is used to locate stroke relationship error and provide correct recognition output together with necessary error feedback. The 5th column, stroke pattern is used to identify which stroke sequence was inputted and if they made any mistake then it provides colorful feedback to students about their wrong writing. Also, it identifies the reverse stroke direction errors by checking the negative value in stroke pattern column (5th column in Table 2.3). All of this error detection mechanism will be discussed as below.

In our online handwriting recognition engine, we used client-server interface to extract the feature points and relevant structural information as (x, y) coordinates along the trajectory of the input device (e.g., pen, mouse, finger etc.) onto the digital web interface. Then, we convert it to angular feature and match those angles with the angular features of preselected template characters and obtain a matching distance between them. In our hierarchical recognition algorithm, we applied multiple filters to reduce the recognition search space.

In Filter II, all of the handwriting input patterns were matched with the multiple patterns of predefined structural dictionary using their positional condition (Table 2.3, 4th column). First our recognition engine obtain a matching distance between input character and structural patterns, and then selects the candidate character for final matching which have the minimum matching distance. If the inputted character was matched with erroneous structural patterns, then our algorithm can detect the committed error by using the pattern index of structural dictionary (index 0~5, as shown in Table 2.3), and immediately send the colorful error feedback about their mistakes. Below is the mathematical notation of above algorism:

$$k = \underset{k \in K}{\operatorname{argmin}} \{s_k\} \tag{7}$$

K=Total number of template characters

k =Student's k^{th} sample character

s_k=Matching distance between inputted character and structural patterns of predefined structural dictionary

As we discussed above, the character with optimal s_k is selected for final matching and thus the corresponding index number can easily be identified. After the identification of index number, the relevant stroke pattern can also be located from the 5th column of Table 2.3. Then we return the feedback to students about their writing mistake by marking the wrong strokes with different colors (6^{th} column in Table 2.3). If the identified stroke pattern has any negative value then our recognition engine can detect that the student has inputted a stroke with reverse direction. Then it returns feedback to students by marking the reverse strokes with red color. After the identification of reverse stroke direction, our recognition algorithm reverses the angular feature of corresponding template characters and matches with the reversely inputted stroke's data of sample characters. In our system, angular feature of original template characters is stored into an array ***t***. After the detection of reverse stroke direction, our algorithm automatically converted angular feature of original template characters using a common angular conversion rule (angle + 180°) and stored into an array ***r***. Then we match the student's input stroke with corresponding reversed stroke of template characters.

Thus, our recognition engine can successfully accept the reverse stroke input and provide students the correct recognition result. In a similarly way, our algorithm can detect and send feedback for the stroke relationship errors, such as stroke with extra length as shown in Table 2.4. For example, in case of Bengali characters অ[a], the second stroke position is bottom of the first stroke. In correct recognition case, it satisfies the condition of y2>b1 (y2-b1! in 4^{th} column) where *y2* is the start point of second stroke and *b1* is the central point of first stroke. From the student input stroke data, our automatic error detection engine can judge that whether y2>b1 or not. If y2>b1 then handwriting was correct otherwise there have a stroke relationship error and then feedback to the students by marking the inputted stroke with blue color. In this way, our proposed intelligent handwriting education system can successfully provide the error feedback together with recognition output.

2.3.3 An Example of Automatic Stroke Error Detection

The following Table 2.6 is an example of structural dictionary for Bengali character "ছ(cha)" to identify split stroke error and generate appropriate student's feedback. As shown in Figure 2.12, miss recognition occurred while students write Bengali characters "ছ(cha)" using 3 strokes. In this case, split stroke error occurred and it triggered the miss recognition. Here, there have two challenges that needed to be considered, one is correct recognition and another one is split stroke error feedback. We used multi-template to recognize split stroke characters correctly. To identify the split stroke input, we assigned the structural dictionary index with large value (50 in below table) together with stoke order column as 202 and 203. Our automatic stroke error detection algorithm identified the order column data with larger value and feedback that split stroke using purple color.

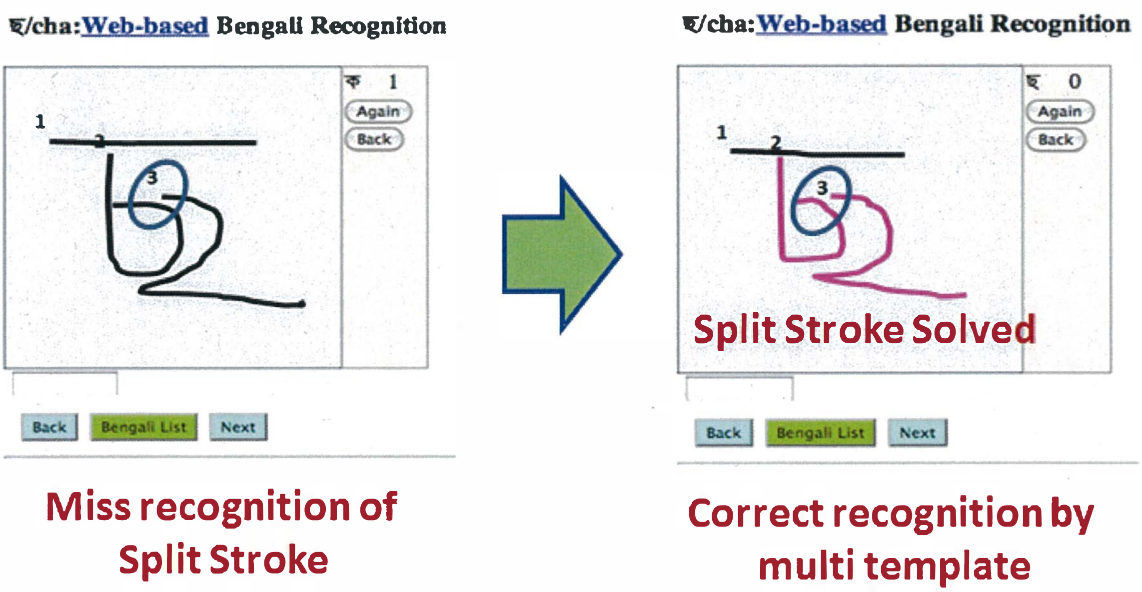


Figure 2.12: An example of automatic error detection and colourful error feedback to correct student's erroneous handwriting of Bengali characters "ছ(cha)" considering split stroke error.

Table 2.6: An example of structural dictionary for Bengali Character“ছ(cha)” to identify split stroke error

#Unicode	Char.	Index	Positional Condition	Stroke Order	Comments
099B 0000	ছ	0	| b2-b1! i2-a1!	| 1 2	|#Correct
::	::	::	::	::	::
099B 0000	ছ	5	| b1-b2! i1-a2!	| 2 1	|#Order Error
099B 0000	ছ	50	| b2-b1! x3-i2! a2-i1!	| 1 202 203	**|#Split Stroke**

3 LEARNING SYSTEM EVALUATION

In this section, we explain the performance analysis of our proposed Bengali handwriting education system considering our survey results in Bangladesh.

3.1 Data Acquisition

For the system evaluation, we have conducted the experimental analysis using the design data set and test data set. We have collected handwritten patterns of Bengali characters from different students where the students of design data set and test data set were different. Handwritten character samples of 21 students were used as design data set and 24 student's data were used as test data set. We have conducted a survey in Bangladesh for the acceptance our learning system, collect student's handwritten data as test data set. Our developed digital web canvas together with PostgreSQL database technology was used to collect student's handwriting data. The following table shows the detail of our used data set. Bengali basic character (chad◌ঁ) is a nasalization marker that appears over the top of an independent vowel or consonant. In our experiment, we considered 49 basic Bengali characters except (chad◌ঁ) . Table 3.1 shows the detail of design and test data set.

Table 3.1: Detail of Design & Test Data Set

#	**Data Category**	**Student's Type**	**Number of Character**	**Number of Students**	**Number of times**	**Number of database**
1	Design Data Set	Bangladeshi People Lived in Japan	49	21	10 Times	10290
2	Test Data set	Lived in Bangladesh	49	24	2 Times	2352

3.2 Experimental System Functional Specification

The following Table 3.2 shows the system specification of prototype designing for our experimental analysis. We used the private WiFi for data collection and experimental survey in Bangladesh.

Table 3.2: Functional specification of prototype designing for experimental analysis

#	Item	Server	Client
1	Internet Usage	Private WiFi	Private WiFi
2	Device Type	MacBook 【Mac OS X 10.6.8】	iPhone 【iOS9.0.8】
3	Web Technology	HTML5, JSON	HTML5, JSON
4	Web Software	Apache Tomcat	Safari/ Chrome
5	Database	PostgreSQL	-
6	Java	Java SE	-
7	Hardware CPU	2.26 GHz Intel Core 2 Duo	-
8	Memory	4 GB	-
9	HDD	240 GB	-

3.3 Experimental System Design Specification

The following Table 3.3 shows the detail design specification of prototype system. During the experimental analysis, we did not find any merge stroke characters.

Table 3.3: System design specification for experimental analysis

#	**Item**	**Number**
1	Total number of Bengali characters	*K*=49
2	Total number of angular templates	59 = (10*2+39)
3	Number of reverse angular template	Automatically calculate
4	Minimum number of preselection rule for each Bengali character	8
5	Number of character for split stroke	3
6	Number of character for merge stroke	0

3.4 Performance Analysis Using Design Data Set

Table 3.4 gives the experimental results of our proposed system using the design data set. In our recognition engine, we applied writing speed free DPM algorithm together with hierarchical preselection. We noticed that our proposed recognition methodology achieved the highest recognition accuracy for every top choice; particularly it achieved 95% accuracy considering Top3 choice. Moreover, the recognition time is significantly reduced to 40 ms/character. These facts ensured that proposed hierarchical recognition scheme with DPM reduced the inherent computational complexity and speed up our recognition engine to adapt with web-based Bengali education system.

Table 3.4: The experiment results of our web-based recognition engine (Scheme1: DPM algorithm with hierarchical preselection)

Recognition Scheme	**No. of Database**	**Recognition Accuracy (%)**			**Speed (ms/character)**
		Top 1	**Top 2**	**Top 3**	
Scheme1	10290	87%	92%	95%	40 ms

3.5 Performance Analysis Using Test Data Set

We have conducted a survey for the acceptance of our web-based Bengali handwriting education system in Bangladesh. For test data set, we have collected handwritten character patterns from 24 Bengali native students of 4 different age groups with respect to age, education and gender together with their questionnaires. During this survey, each student has written almost two times of every Bengali character sample, 12 of them has written two or more times. In this survey, we have collected the student's individual scores in terms of "Simplicity", "Recognition Speed", "Colorful Error Feedback", and "Effectiveness" of our Bengali handwriting education system.

Table 3.5: The range of student's evaluation score in terms of MOS (Mean Opinion Score)

MOS	**Quality**	**Impairment**
5	Excellent	Imperceptible
4	Good	Perceptible but not annoying
3	Fair	Slightly annoying
2	Poor	Annoying
1	Bad	Very annoying

Table 3.5 shows the range of student's evaluation score in terms of MOS (Mean Opinion Score). Here, the student's evaluation score is ranged from 1 (Bad) to 5 (Best), and separated as "Bad" (Score 1), "Poor" (Score 2), "Fair" (Score 3), "Good" (Score 4) and "Best" (Score 5). We have conducted our survey within the people of different age group, such as 5~15 years old, 15~30 years old , 30~50 years old and 60~70 years old people.

Table 3.6: The snapshot student's evaluation score in terms of MOS (Mean Opinion Score) for the age group 5~15 years old

Student's Initial Name	Student's ID	Student's No.	Student's Age	Simplicity	Speed	Feedback	Effectiveness	Total MOS	Average MOS for Age Group
S1	27		6	4	3	5	4	4	
A	34		7	3	4	5	4	4	
S2	41		7	5	5	5	5	5	
S2	26		8	3	4	5	4	4	MEAN= 4.4
R2	25	9	10	3	4	4	5	4	
M1	42		10	5	5	5	5	5	S.D.=0.5
H	20		11	4	4	4	4	4	
R2	21		11	5	5	5	5	5	
M2	39		12	4	5	5	5	4.75	

Table 3.7: Student's MOS matrix based on 4 different evaluation terms

Student's Age (Years)	Average MOS for Simplicity	Average MOS for Speed	Average MOS for Feedback	Average MOS for Effectiveness	Average MOS of Each Age Group
5-15	4.0	4.3	4.8	4.6	4.4
15-30	4.3	3.7	3.7	3.0	3.7
30-50	4.4	3.6	4.2	3.8	4.0
50-70	4.3	4.3	4.4	4.9	4.5
Average MOS	4.3	4.0	4.3	4.1	4.1

We have categorized the student's questionnaire data based on different age group and then analyze their MOS data for the evaluation of our proposed

Bengali handwriting education system. Table 3.6 shows the snapshot of student's evaluation score for age group 5~15 years old in terms of "Simplicity", "Recognition Speed", "Colorful Error Feedback", and "Effectiveness" of our Bengali handwriting education system.

Table 3.7 represents the student's MOS matrix based on 4 different evaluation terms. Here, the MOS (Mean-Opinion-Score) data was calculated by the arithmetic mean of all the individual scores for 4 different evaluation terms. As shown in Table 3.7, the average MOS value in each term is above 4.0. It confirmed that our proposed Bengali handwriting education system achieved "Good" in all evaluation categories. In addition, the students of age 5~15 years old and age 60~70 years old have the higher MOS of 4.6 and 4.9 respectively in terms "Effectiveness" whereas the students of age 15~30 years old and age 30~50 years old have the lower MOS of 3.0 and 3.8 respectively. It ensured that the children and older people who do not have the chance to go to school liked our education system more than the middle aged students. We further analyze the questionnaire's MOS data together with handwritten character recognition accuracy of 24 people of different age in next part.

As we described above, all of the handwritten character samples and questionnaire's MOS data were stored in our database table. We have executed an experimental analysis of that test data set (2,352 handwritten characters samples) by using our developed recognition batch program and stored the recognition results of each student in another database table. Then, we calculated the recognition accuracy (%) of every writer together with their provided MOS value from the database table where we have stored all the recognition results during the execution of recognition batch program. The following Table 3.8 shows the surveyed results of student's evaluation score in terms of average MOS together with the average handwriting recognition accuracy (%) of 4 different age groups. For the performance analysis, we have calculated the student's recognition accuracy into two separate parts, 1st trial handwriting recognition accuracy (%) and 2nd trial handwriting recognition accuracy (%). It was calculated by using the 1st time and 2nd time handwriting test data set of each writer respectively. We considered the student's MOS value and their 1st trial and 2nd trial handwriting recognition accuracy as system evaluation parameters.

As shown in Table 3.8, the students of age 5~15 years old and age 60~70 years old have the MOS value of 4.4 and 4.5 with 2nd trial handwriting recognition accuracy of 91.1% and 95.3% respectively. Oppositely, the middle age students (15~30 and 30~50 years old) have the low recognition accuracy with low MOS value. It ensured that the students with higher recognition accuracy have the higher MOS values and the students with low recognition accuracy have the lower MOS values. This result also confirmed that the average of 2nd trial handwriting recognition accuracy (average 91.4%) was improved compare to 1st trial handwriting recognition accuracy (average 87.2%) for each age group, and the average improvement was 4.1% by using our autonomous learning methodology.

Table 3.8: Student's survey results for the acceptance of web-based Bengali handwriting education system together with the average recognition accuracy of each age group

Student's Age (Years)	**No. of Students**		**1st Trial Handwriting Recognition Accuracy (%)**	**2nd Trial Handwriting Recognition Accuracy (%)**	**Improved Recogniton Accuracy (%)**	**Average MOS of Each Age Group**	**Standard Deviation(S.D.)**
5~15	9	24	89.1	91.1	2.0	4.4	0.5
15~30	3		81.1	89.2	8.1	3.7	0.6
30~50	5		82.5	85.2	2.7	4.0	1.0
50~70	7		88.9	95.3	6.4	4.5	0.5
Average	6.0		87.2	91.4	4.1	4.1	0.7

This improvement was achieved due to the colorful error feedback about student's handwriting errors for their 1st time handwriting. The students can successfully notice their handwriting mistakes of stroke order or stroke direction. Then, they can correct their handwriting in 2nd trial, and thus the 2nd trial handwriting recognition accuracy was improved. Figure 3.1 shows the scatter plot of 1st trial and 2nd trial handwriting recognition accuracy (%) of every student to analysis the performance improvement of our proposed Bengali education system. As shown in Figure 3.1, the trend line is moving in the positive direction and it achieved the positive gradient with "strong" positive correlation where the larger values of 1st trial handwriting recognition accuracy data (x-axis) are associated with the larger values of the 2nd trial handwriting recognition accuracy data (y-axis). It depicts that 2nd trial handwriting recognition accuracy (%) was improved compare to 1st trial handwriting recognition accuracy (%) for almost every students, and the average accuracy was improved by 4.1% (Table 3.8).

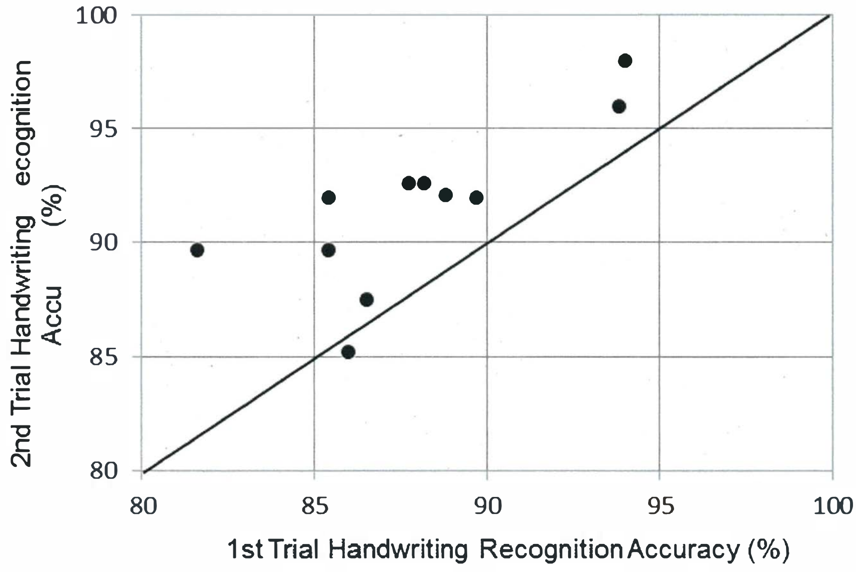


Figure 3.1: The scatter plot of 1st trial and 2nd trial handwriting recognition accuracy (%) of 12 students to analysis the performance improvement for our proposed Bengali education system

Moreover, the students of age 5~15 years old and age 60~70 years old have the MOS value of 4.4 and 4.5 with standard deviation 0.5, and the students of age 15~30 years old have the MOS value of 3.7 with standard deviation 0.6 (Table 3.8). It depicted that most of the students in Bangladesh, especially children or older people, who do not have chance to go to school, liked our Bengali education system to practice Bengali handwriting characters. On the other hand, the middle age students (15~30 years old) have the low MOS value with higher standard deviation, it illustrates that most of the people aged 15~30 years old are literate and their opinion is fluctuating. But, the literacy rate of children or older people are very lower compare to middle age people, and they can learn without teacher supervision at anywhere at any time and they can correct their committed error using real time colorful error feedbacks. In addition, they can repeat the same exercise several times to speed up their learning process. The above analytic results confirmed that our proposed web-based Bengali education system is highly appreciated by the illiterate people in Bangladesh. Moreover, the total average MOS for all aged people has the value of 4.1 with the standard deviation of 0.7. This value ensured that almost every user evaluated our system as "Good" (Score 4).

The following Figure 3.2 shows an example of autonomous learning of Bengali characters অ (a) which has the three individual strokes. Since the second stroke of this character has a similar shape with other Bengali characters, handwritten mistake is very easy to occur. In our survey, almost 8 people made the stroke order mistakes between 1st and 2nd strokes of Bengali characters অ (a) for almost two or three times. Also, 4 of them have made the stroke direction mistake for the 2nd stroke of অ (a) for three times. Our autonomous learning tool can successfully send the colorful feedback about the student's handwriting errors Figure 3.2 (left side), and the students can correct their own mistake by themselves as shown in Figure 3.2 (right side). In our proposed Bengali education system, we are aimed to teach our students correct and attractive handwriting style automatically that makes the students be able to write good balanced Bengali handwriting characters. For instance, the second stroke of Bengali character ভ (bha) and চ (ca) has similar handwriting shape. It's starting and ending points are opposite from each other. Reverse handwriting input of second stroke of "ভ(bha)", turns it into the Bengali characters "চ(cha)" and vice versa. This kind of miss handwriting input creates lots of miss understanding between Bengali characters. So, the stroke's error (e.g., stroke direction, order, split or merge errors) should be detected to teach our students correct and attractive handwriting style.

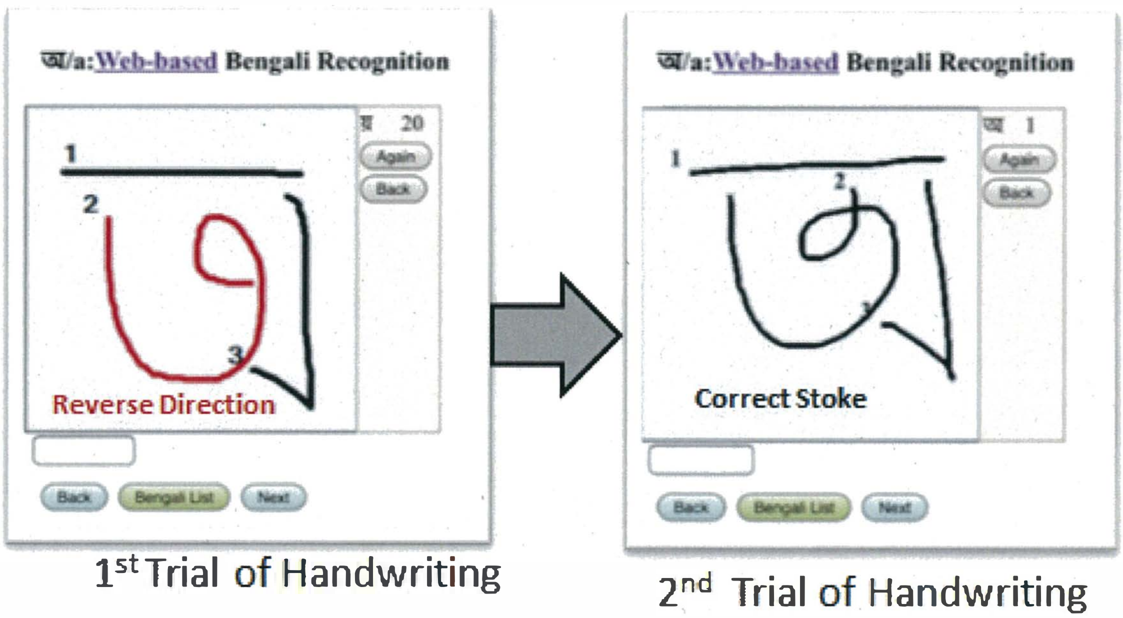


Figure 3.2: An example of autonomous learning of Bengali characters অ (a)

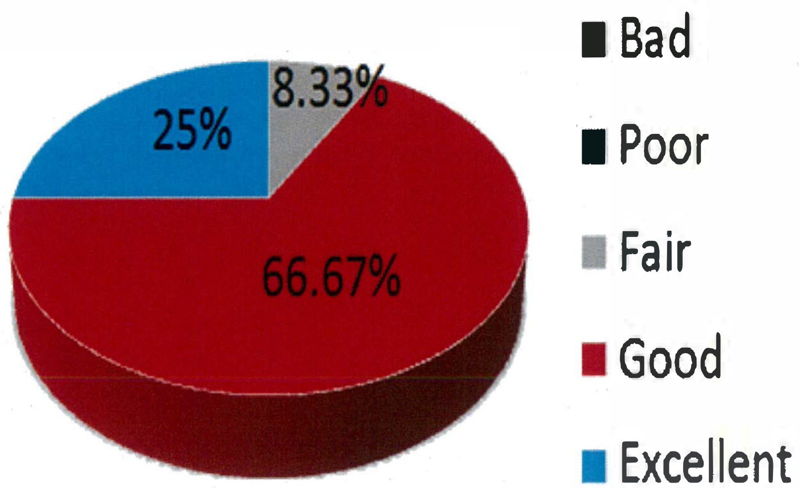


Figure 3.3: Bengali education system user rating based on student's questionnaire data.

The above Figure 3.3 showed the Bengali education system user rating based on student's questionnaire data. 66.67% of student's evaluated our system as "Good" and 25% of them evaluated as "Excellent" and rest of them as "Fair".

4 CONCLUSION AND FUTURE WORK

In this paper, we have described the effectiveness of autonomous learning methodology for the literacy improvement by using our proposed web-based Bengali handwriting education system. It ensured the autonomous learning of Bengali handwriting characters at anywhere at any time for those population, who do not have chance to go to school, especially children or older people. Here, we developed a web-based (iPhone/smartphone or computer browser) intelligent handwriting client-server interface using JavaServer Pages technology for autonomous learning of Bengali handwriting characters. Our experimental analysis showed that the use of colorful error feedback methodology helped to improve the average recognition accuracy by 4.1% (improved from 87.2% to 91.4%) with average Mean-Opinion-Score of 4.1. Also, our proposed hierarchical recognition algorithm together with writing speed free DPM improved the average recognition accuracy up to 95% as well as recognition speed of 40ms/character for Bengali basic characters. It makes our recognition algorithm adaptable for the application of web-based language learning. Our automatic error detection methodology ensured the necessary feedback to the students to learn about their handwriting mistake autonomously. Since all of the population, especially children and older people do not have the chance to go to school in Bangladesh. So, schooling system is not enough to achieve the 100% literacy improvement. The successful use of web-based Bengali handwriting education system can help to achieve 100% literacy improvement in Bangladesh within a very short period.

In future, we will focus our research to improve the recognition accuracy. To implement student's feedback methodology regarding stroke order free and stroke direction free recognition, miss-recognition possibility was increased. In our future work, we will apply the fuzzy rule to build structural dictionary. In addition, we will focus our research on the development of Bengali handwriting education system considering Bengali syllabic and compound characters, which are consonants, & vowels combined shape to support Bengali word learning. Finally, my system will contribute national literacy and further advancement of the status of woman through educational improvement.

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1. Journal Full Paper

Nazma Khatun & Jouji Miwa. An Autonomous Learning System of Bengali Characters Using Web-Based Intelligent Handwriting Recognition. Journal of Education and Learning , Vol. 5, Issue 3, pp. 122-138 (May 10, 2016).
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