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Research Article

Real-time feedback engine for online jawi character recognition

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Abstract
Jawi is a type of cursive writing derived from the Arabic alphabets and adopted for writing the Malay language. The Jawi alphabet has 36 basic characters, in which 28 characters are similar to Arabic characters. Studies on online Jawi characters recognition are still minimal; most studies focus more on offline. Therefore, the online Jawi characters recognition engine has developed, involving two stages; the template modelling process and the recognition process using matching templates. The recognition engine developed can provide real-time feedback on the accuracy of Jawi characters writing activities by users. The recognition engine's feedback accuracy assessed using a comparative analysis method by looking at the agreement score between recognition engine feedback and experts' feedback. The Krippendorff's Alpha Reliability Coefficient Index (Krippendorff's α) agreement score was used to measure the agreement between the recognition engine feedback and experts' feedback. Krippendorff's α agreement score assessment results found that the accuracy of recognition engine feedback was almost the same as the experts' feedback. Therefore, it can conclude that the recognition engine developed has high accuracy and can be used to recognise Jawi characters online.

Keywords
Online, Jawi characters, Recognition engine, Feedback, Agreement score.

1.Introduction
Jawi is a type of cursive writing derived from the Arabic alphabets and adopted for writing the Malay language. Jawi writing adopted presently has undergone an adaptation or an assimilation process with the Malay speech community in Malaysia. Jawi is written and read from right to left like the Arabic writing system. The Jawi character has 36 basic characters, in which 28 characters are similar to Arabic characters. The history of education in Malaysia shows that Islamic education has been taught either by books or texts written in Jawi script, which is still used today. However, research on Jawi writing for children is still limited [1].

Furthermore, the lack of learning materials and studies of writing Jawi contributes to the negative perceptions of the younger generation [2].

Learning Jawi is not only serves in mastering a part of Islamic education, in fact, it is a medium for dignifying Jawi as the nation's cultural heritage art [3]. According to similar research, children's writing skills can be improved by learning Jawi writing skills [4]. Among the benefits of learning to write in Jawi can be seen in terms of fine motor development and improving the skills of reading the Quran as Jawi is a continuation of writing and reading Arabic characters adapted to the English language [5].

The Jawi writing lesson should also be stressed while constructing each character's correct formation and sequence. James and Engelhardt [6] suggested that the most critical information in handwriting is stroke information rather than shapes. Amin et al. [7, 8], the existing approach is insufficient in stressing crucial parts of fundamental Jawi handwriting abilities, such as writing in proper sequences and lacks evaluations throughout the writing process. Many movement flaws might be caused by a lack of appropriate

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fundamental handwriting at an early stage. Students will have difficulty combining characters to form words in subsequent writing Jawi lessons when the fundamental character is generated with the wrong movement or direction. Jawi's teacher can verify students' writing by looking at the shapes of the character they make. On the other hand, teachers cannot determine the correct stroke order unless they are there during the writing process [7]. It also demonstrates that the existing system is overly reliant on instructors' talents and presence in learning and evaluation processes.

The advantages of touch screen technology capable of providing real-time feedback are suggested in the study of Jawi writing. With digital learning, students would benefit from both traditional active learning methods and digital tools that support a multitude of disciplines for Jawi learning. Our main objective is to recognise and analyse Jawi handwriting online by providing real-time feedback on the correct way of Jawi character formation, from the beginning of character formation to the end of character formation, according to Jawi writing standards. The proposed real-time feedback engagement requires the use of algorithms and recognition techniques to provide accurate feedback on the writing entered. The accuracy of the feedback generated by the recognition process must be evaluated to determine if the recognition engine developed can be used to learn to write Jawi.

The study is organised as follows. Section 2 the literature and motivation of this work. Section 3 presents the methodology of the real-time feedback engine for the online Jawi character recognition process is divided into two processes: the template modelling process and the characters recognition process. Result of the accuracy for the real-time recognition process in section 4. Section 5 presents the discussion on the obtained results as well as the limitations of this work. The paper finishes with the conclusion and scope of future work in section 6.

2.Literature review

Jawi, character recognition research, has started since the end of the 1990s [9, 10]. Since then, many studies have been proposed in recognition of the Jawi character. Most studies concerning Jawi recognition were related to offline recognition. Razak et al. [10] applies the discrete wavelet transform (DWT) method and Hamming classification for offline Jawi handwriting recognition. Redika et al. [11] studied offline handwritten Jawi word recognition using hidden Markov models, while Heryanto et al. [12] developed an offline Jawi recognition system using hybrid artificial neural networks and dynamic programming. Razak et al. [13] also introduced a k-mismatch algorithm, recognising characters on a chip design based on the offline Jawi writing extraction features. Nasrudin and Petrou [14], using future invariants for offline Jawi character recognition and offline handwritten Jawi recognition using the trace transform. Arnia et al. [15] research to the improvement of binarization performance in pre-processing and continue studying the performance of pattern classifiers in offline Jawi character recognition using an algorithm based on Hu's moment as an invariant feature. A recent study on Jawi handwriting by Hasan et al. [16] continues on offline Jawi handwritten recognition focused on trace transform feature learning. All Jawi offline recognition studies focus on the performance of pattern classifiers in Jawi recognition to achieve the highest accuracy with various algorithms and techniques.

The early online Jawi characters recognition study was conducted by Ahmad [17], aiming to assist essential Jawi learning by Jawi illiterate users. However, the recognition process produced only recognised non-cursive Jawi characters, with the input from mouse movements. Saddami et al. [18] developed a database of handwritten Jawi characters, words, and sentences. The development of this data collection is a step toward bringing Jawi writing into the world of online Jawi recognition. Muchallil and Nazaruddin [19] compare Jawi's online and offline performance of handwritten character recognition based on the time required to extract features from a character image. The result indicates that the online programme outperforms the offline application in terms of performance and that the online application is capable of extracting the moment feature of handwritten characters. Rahim and Hamzah [20] investigated the use of online Jawi writing recognition to create an interactive tool for learning how to write Jawi character. The technique stores the coordinates and sequence of strokes for each Jawi character in the database. During the user's input of the Jawi character, the coordinates (x, y) of the pixels representing the drawn Jawi alphabets are used to calculate and normalise the slope values of these coordinates. Target users have evaluated this application for its design look, learnability, and ability to assist learners with computer-based writing activities. Several online Jawi character recognition studies have been implemented, although these are still in the early stages of development. However, it serves as a starting point for further innovation of Jawi character recognition engines.

Most previous studies on Jawi writing focused on the features of stroke because Jawi writing is cursive writing with many curves. Almost all Jawi characters resemble Arabic characters; only some characters have the same shape but differ in the number of dots and the position of the dots [21, 22]. The Arabic and Jawi characters share complexity because the form, position, and handwriting style depends on the individual's handwriting [17, 22]. Therefore, studies on Arabic character recognition can be used to extend the Jawi recognition study. In Arabic and Jawi, some characters may have an isolated beginning, middle, or end form. Each character has different forms according to its position in a given the word.

Moreover, each Arabic writer has a specific writing style, and the same writer can write many styles. In other words, the writing style is usually unpredictable and difficult to recognise using the previously developed algorithms [23]. Characters like Jim (ج), Shin (ش), and Ta (ت) have one to three dots. Also, the location of these dots is different. For example, a dot can be found above, under or within the character body [24]. Therefore, Elanwar et al. [25] used a rule-based method, while the features extraction process was carried out based on three data formats from the freeman chain codes (FCC) algorithm. The first code represented a long-stroke, the second described a short-stroke, while the third referred to when the pen was lifted. The results showed 92 per cent character recognition accuracy, with similar accuracy for strokes and 77% accuracy for words. According to Lawal et al. [26], an average rate of 99.03 per cent automatic recognition of Arabic characters was achieved using a set of 32 features based on FCC codes. Althobaiti and Lu [23] introduced a method based on Freeman chain coding to recognise online handwritten Arabic characters. Previously published works [27] used Freeman chain coding for the same purpose. According to Darmawan et al. [28] Freeman Chain Coding is widely used in image processing to represent lines, curves, or edges of an area and save memory. Their study found that Arabic character recognition reached 60% and above with the use of this method. Afrianto et al. [29] also successfully used Freeman chain code to perform feature extraction on an Arabic character by representing contour shapes. The results obtained in these works were promising, in addition to transforming the Arabic character into a series of numbers reflecting its various changes in direction, and that is what we see in line with the curved nature of Arabic writing [30].

Features are extracted from the image of a character which is expected to represent the shape of the images. This information goes onto the classifier to help in the classification process. The feature extraction phase of the study applying FCC promises appropriate recognition outcomes, and hence the classification phase should be determined to ensure precise findings. Consequently, Elanwar et al. [25] carried out the Arabic handwriting recognition system based on a decision tree technique to identify words from handwriting. Each character was specified for the feature extraction phase with the number of direction codes from one to four and a code split (0). Each character had its codes collection, named according to their respective number codes. The decision tree was then used to store the character's code information for the recognition process. The respective tree node had five branches corresponding to five numbers from 0 to 4 in the number code. The system was only tested on 13 Arabic characters based on four words used as postcodes in some Arab countries, with an average accuracy of 86 per cent. Sternby et al. [31] used a decision tree technique and found this technique suitable for mobile devices for online Arabic handwriting recognition. Omer and Ma [32] also used the decision tree and matching algorithm to recognise online Arabic characters handwriting. The decision tree made faster classifications in recognising characters and reduced features implementation processing time. The researchers also used the FCC algorithm to represent each stroke to extract features. The recognition process used a matching algorithm based on a stroke direction string equation, resulting in a high accuracy rate of over 80 per cent [33]. Then a similar study by [34, 23], Freeman code was proposed to calculate similarity according to the printed characters. In order to enhance the obtained recognition rate, a template matching method for the recognition of handwritten Arabic characters is considered. These new features have improved the recognition rate remarkably from 80.78% to 95.89%.

Approaches and techniques for recognising Arabic characters can be adapted for online Jawi characters recognition. The feature extraction process method using the FCC algorithm can be used given its sound accuracy level. Pattern matching recognition and decision tree methods can be used for the online Jawi characters recognition process because of their ability to provide fast and accurate feedback on tablet devices. The recognition method and technique described can help the online Jawi characters recognition process.

3.Methodology

The character recognition process is performed to get feedback on how to write correctly and recognise the characters entered when writing Jawi characters. More than one algorithm and technique are used to develop the recognition engine. Since mobile devices and tablets are used, coding and programming logic skills and competencies are required. The online Jawi characters recognition process is divided into two processes: the template modelling process and the character recognition process. A detailed explanation of each process is discussed in the subsequent sections.

3.1Template modelling process

The process of online Jawi characters recognition template modelling involves six stages. Each stage and activity involved can be seen in *Figure 1*. A detailed explanation begins with the first stage, obtaining the data sample using a digitizing tablet. Ten respondents comprising four adults and six children were involved. A prototype was developed to record the respondents' movement input to help facilitate taking data samples. This prototype used a graphical environment in a mobile device, the 10-inch Galaxy Note 2, name "See Floor". Respondent wrote Jawi characters eight times using the "See Floor" prototype. Then, the outcome of Jawi characters writing was verified by a Jawi expert to ensure that the sample produced is following the correct standards of the Jawi characters writing process.

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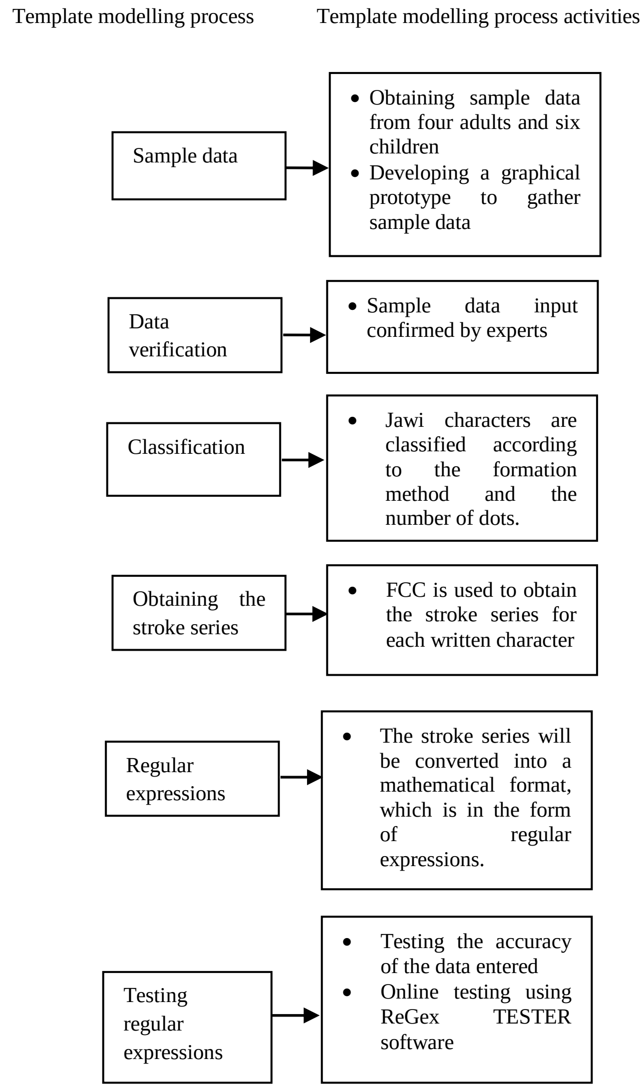

Figure 1 Brief explanation of template modelling process activities

Jawi characters are curved characters, and some characters are almost identical in terms of shapes but different in terms of the number of dots. Since the shapes are identical, the way of writing is also indirectly the same; thus, the almost identical characters are classified according to ways of formation groups. There were 32 Jawi characters written by the respondents classified into 16 groups according to the way of writing and then arranged according to the number of dots and their positions, as shown in *Table 1*.

Table 1 Jawi Characters are divided into groups based on the number of dots and their positions

Jawi characters group	Same character group	Number of dots	Dots position
1	ا	no dots	-
2	ت ب ث	one dot two dots three dots	upper dots lower dots
3	ح ج چ	one dot two dots three dots	upper dots lower dots
4	د ذ	no dots one dot	
5	ز ر	no dots one dot	upper dots
6	ش س	no dots three dots	upper dots
7	ص ض	no dots one dot	upper dots
8	ظ ط	no dots one dot	upper dots
9	ع غ ڠ	no dots one dot three dots	upper dots
10	ق ڤ ف	one dot two dots three dots	upper dots
11	ل	no dots	
12	م	no dots	
13	و ۏ	no dots one dot	upper dots
14	ء	no dots	
15	ک ڬ	no dots one dot	upper dots
16	ى ي	no dots two dots	lower dots

Upon entering by the respondents, all sample data were verified by an expert, known as the recognition sample (RS). The RS contained the movement direction and features of all studied Jawi characters. The data obtained was a string of strokes generated during the writing process.

A string of strokes following the trajectory of the pen position is considered producing a complete character. Stroke is defined as a sequence of horizontal and vertical coordinates occurring consecutively, clearly showing the up and down pen movement [35]. The FCC algorithm was used to obtain the string of strokes written by the respondents. FCC represents boundaries with sequences connected by long straight-line segments and defined directions [36]. Typically, representations are based on four or eight connected segments, and the direction of each segment is coded using a numbering scheme [37]. The boundary code is formed as a sequence of directed numbers called the FCC, which is a boundary chain code depending on the starting point when writing. The eight representative segments were used in this study, and the numbering scheme started with number one, as shown in *Figure 2*.

During the characters formation process, a string or series of stroke directions was obtained from the FCC for a Jawi character formed by the respondents.

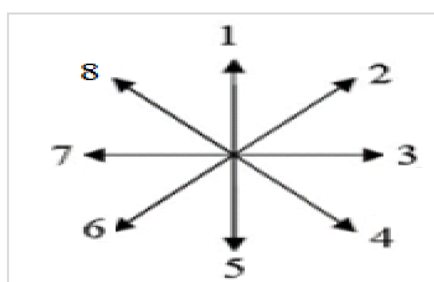

Figure 2 FCC numbering scheme used in the study

After the stroke series for each character was obtained, the FCC number sequence stroke series will be converted into a mathematical format, which is in the form of regular expressions. The written regular expressions for each character, resulting from a series of character strokes from the ten respondents, were verified by experts. The regular expressions produced for each character formed in this study contribute to recognising the Jawi characters. Refer to *Table 2*, which displays the regular expression in mathematical format for some of the characters used in this study.

Table 2 Regular expression in mathematical format for 6 group of Jawi character

<table>
<tr><th>Jawi characters group</th><th>Same character group</th><th>Regular expressions</th></tr>
<tr><td>1</td><td>ا</td><td>5</td></tr>
<tr><td>2</td><td>ث ت ب</td><td>(4|5)+6×78*(1|2) + (09) {1,3}</td></tr>
<tr><td>3</td><td>چ ج ح</td><td>(1|2)*36*7*654(3|2)*</td></tr>
<tr><td>4</td><td>ذ د</td><td>4(5|6)*7</td></tr>
<tr><td>5</td><td>ر ز</td><td>4*567*</td></tr>
<tr><td>6</td><td>ش س</td><td>(5(6|7|8)+1*2*){3}</td></tr>
</table>

The regular expressions were tested to ensure that the accuracy of strokes from the FCC entered by users could be identified in the recognition process. The testing was conducted using REGex TESTER software [38], obtained free online. Various possible test datasets were included to test the accuracy of the produced regular expressions. Upon completing the testing process, the constructed regular expressions were used in the following process, the recognition process.

3.2Recognition process using matching templates

The recognition process is to obtain feedback related to writing and recognising the characters written by users. The Jawi characters recognition process begins when users start to write on the touch screen directly online and is represented as a stroke or a combination of strokes with dots. In this study context, a stroke is defined as the trajectory occurring at the tip of the pen when it first touches the written surface until the earliest time the touch on the written surface ends.

Next, the recognition engine development process, as can be seen in *Figure 3*, is discussed with an explanation of each process given in stages:

- **Data acquisition**

Online writing recognition is immediate writing recognition while users write. Users write text on a digitiser tablet or a sensitive touch device, recording the data coordinate of positions of the tip of the pen movement as soon as the users write. Subsequently, the system recognises the writing.

The writing process is done in real-time; thus, the characters are straight away converted into other formats as a function of time. When users write on the screen using a stylus pen, the signal is converted into coordinates in the function of time, with x and y positions. Therefore, data acquisition is an important stage in the recognition process, especially in the online recognition system. Various digitisers with different technologies are available because digitiser tablets cover various uses based on application and reliability [39]. This study's data was obtained using a mobile device, namely the 10-inch Samsung Galaxy Note 2, to facilitate children writing Jawi characters.

- **Pre-processing**

After the input data has been observed and digitised in the data acquisition stage, the recognition process involves the second stage, pre-processing. In this stage, users' input data is in a clean state from interference; thus, it is easier to process in the next stage. According to [40], the pre-processing stage is performed to eliminate or reduce as many data interferences and changes as possible due to the sequence of points obtained. Most digitisers do uniform sampling temporarily only. It is because problems occur while conducting the sampling in the areas in which the pen is moved too slowly and too fast [41].

The pre-processing technique is necessary to improve the handwriting input quality entered by users. The catmull-rom spline algorithm (C-R splines) is used so that the users' writing process runs smoothly and with less interference to overcome this problem. The C-R splines technique is the original set of points forming the spline curve's control point [42]. C-R splines are often used in the computer graphics context to obtain fine movements intervening across the keyframe. C-R splines are easy to assess and the best option for interactive applications because of their ability to intervene control points and subsequently provide an intuitive way to represent and edit curves in an application [43]. A previous study by Vatavu [44] used C-R splines for pattern recognition, parallel line recognition, basic limitations, and sketch-based editing [45].

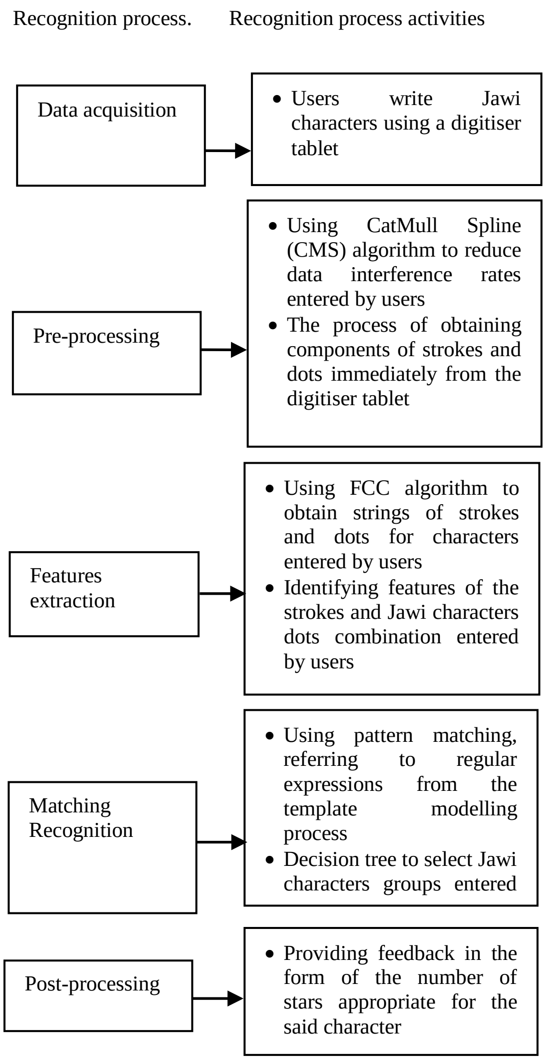

Figure 3 Online jawi characters recognition process

Currently, devices used for online recording are cheap. The outcomes are fine; thus, the pre-processing process is more focused on interference signals causing the sampling process to no longer be a key component in the recognition process. Therefore, the pre-processing process has become simpler, and the results required for the next process are obtained faster.

- **Features extraction**

The FCC algorithm is used to obtain the string of strokes and points entered by users. This process immediately occurs as users write on the digitiser tablet. FCC aims to obtain a string of strokes, which is part of the Arabic characters recognition process used in previous studies [24, 46].According to Omer and Ma [32], each stroke is represented by one FCC direction to produce its features. The strokes and points from the features extraction are already in the data format containing Jawi characters features to be identified. The pre-processing and features extraction processes occur simultaneously when users touch the touch screen to form Jawi characters.

- **Matching recognition**

The recognition phase involves using the pattern matching technique by comparing similarities between stroke strings in the features extraction phase with regular expressions from the template modelling process. If the writing is done following the sequence of strokes equivalent to regular expressions, then the Jawi characters recognition occurs and the characters formed are identified. A similar technique was used in the study by Gupta et al. [47], stating that the online characters recognition method uses directional information to identify the written characters assuming the same directional information is generated if the directional information is rewritten for a second time.

Recognition using pattern matching and decision tree are among the recognition methods used. Pattern matching from regular expressions only recognises the characters basic form in general without dots [31]. The number of dots for each character is identified by using the decision tree technique. The decision tree is arranged according to the characters formation classes, followed by the decision tree branches in terms of the number of dots: no dots, one dot, two dots, and three dots. The decision tree of the study can be seen in *Table 3*.

Finally, the recognition process is successful if it meets all the features identified during the features extraction process. The recognition process determines the characters entered and how to write the Jawi characters to see the recognition results through the post-processing process.

- **Post-processing**

Post-processing is the stage of providing game feedback on users writing outcomes. In the recognition stage, the only process involved is the characters identifying process, but the post-processing stage involves two processes: writing characters and users' writing quality. Game feedback is the number of stars given based on the way of writing and the quality of writing entered by the user. The number of stars given is based on the characteristics that have been set and shown in *Table 4*. The set number of stars is referred Jawi characters to and validated by Jawi writing experts and children's fine motor skills experts.

Table 3 Decision tree and branch to decide to choose

Character formation class	Decision tree branches	No dots	One dot	Two dots	Three dots
ا	One	ا	NA	NA	NA
ب	Three		ب	ت	ث
ح	Three	ح	ج	NA	چ
د	Two	د	ذ	NA	
ر	Two	ر	ز	NA	NA
س	Two	س	NA	NA	ش
ص	Two	ص	ض	NA	NA
ط	Two	ط	ظ	NA	
ع	Three	ع	غ	NA	ڠ
ف	Three		ف	ق	ڤ
ل	One	ل	NA	NA	NA
م	One	م	NA	NA	NA
و	Two	و	ۏ	NA	NA
ء	One	ء	NA	NA	NA
ک	Two	ک	ڬ	NA	NA
ى	Two	ى	NA	ي	NA

Table 4 Evaluation of writing activities using the "number of stars" method

Star rating	Writing character
Zero Star	• There was no writing at all, upside down, and written in the wrong sequence. • Below 20 percent of quality and accuracy of writing
One Star	• Accuracy and quality writing between 21 to 50 percent
Two Stars	• Accuracy and quality writing between 51 to 70 percent.
Three Stars	• Accuracy and quality writing between 71 to 100 percent.

4.Result

The assessment of feedback accuracy of the engine developed used the agreement scores comparison method between the engine feedback or automatic feedback (AFB) and experts' manual marking practices. The study collected data from the constructed recognition engine as the feedback of Jawi characters' writing activities. A total of 800 feedback for 16 Jawi characters groups were collected from 12 selected children.

The agreement score of the Krippendorff Alpha Coefficient of Reliability Index (Krippendorff α) [48−50] is a numerical value that indicates the degree of agreement in this study. A study to assess the manual score reliability was performed before any degree of agreement analysis between AFB and manual marking feedback (MFB) by three experts for Jawi characters writing activities.

The agreement of data accuracy from the three experts is significant in this study since it serves as a standard reference for the human comparison study, ensuring that the agreement rate is not too different. It also acts as a guide in determining the accuracy of the study's data. The degree of agreement values based on Krippendorff's α values for the three experts' manual scores and the 16 Jawi characters groups for characters' writing activities are shown in *Table 5* below. *Table 5* shows the agreement scores of the recognition engine accuracy using Krippendorff's α, presenting the agreement in the form of values. Krippendorff [50] defined the acceptable reliability levels as follows:

$\alpha \geq 0.80$: Data that can be applied (reliable).

$0.67 \leq \alpha < 0.80$: Allowing temporary and reversible conclusions

$\alpha < 0.67$: Unacceptable reliability level

The baseline accuracy level indicated by Krippendorff's reliability coefficient is equal to or greater than 0.70 [51−53]. Referring to this study's Krippendorff's α, all 16 characters groups exceeded the minimum level of 0.70, recording an average Krippendorff's α value of 0.720. Therefore, the elements studied can be applied and suitable for further studies. The next step is to compare the agreement between AFB from the recognition engine and experts' MFB from an expert. The degree of agreement between the AFB score and the MFB score mode for the recognition engine is determined by referring to the Krippendorff α. A comparison between the AFB and MFB score modes was performed for all 16 characters groups to assess Krippendorff's α reliability coefficient values. Krippendorff's α values for all characters' groups from 1 to 16 are shown in *Table 6*.

Table 6 shows that the Krippendorff's α reliability coefficient values for all 16 characters groups are greater than the minimum level of 0.70, recording an average Krippendorff's α value of 0.839. A degree of agreement of 0.839 implies the AFB score reliability is at the highest reliability level. Based on this reliability level, it can be said that the feedback generated automatically by the recognition engine has a high accuracy level and is comparable to the feedback given by the experts manually.

Table 5 Degree of agreement MFB between the three experts

Jawi characters group	**Degree of agreement MFB among the three experts (Krippendorff α)**
1	0.702
2	0.913
3	0.748
4	0.742
5	0.762
6	0.701
7	0.598
8	0.651
9	0.788
10	0.770
11	0.767
12	0.712
13	0.801
14	0.436
15	0.701
16	0.722
Krippendorff $\alpha_{everage}$	0.720

Table 6 Degree of agreement between MFB and AFB recognition engine

Jawi Characters Group	**Degree of agreement between MFB and AFB recognition engine (Krippendorff α)**
1	0.446
2	0.988
3	0.933
4	0.840
5	0.900
6	0.886
7	0.926
8	0.955
9	0.815
10	0.854
11	0.882
12	0.791
13	0.805
14	0.845
15	0.784

Jawi Characters Group	Degree of agreement between MFB and AFB recognition engine (Krippendorff α)
16	0.779
Krippendorff $\alpha_{everage}$	0.839

5.Discussions

The agreement of data accuracy from the three experts is significant in this study since it serves as a standard reference for the human comparison study, ensuring that the agreement rate is not too different. It also acts as a guide in determining the accuracy of the study's data. Krippendorff [50] defined the acceptable indicated by Krippendorff's reliability coefficient is equal to or greater than 0.70 [51−53]. Referring to this study's Krippendorff's α, all 16-character groups exceeded the minimum level of 0.70, recording an average Krippendorff's α value of 0.720 as shown in *Table 5*. Therefore, the elements studied can be applied and suitable for further studies. Average value of 0.839 shown in *Table 6* implies the AFB score reliability is at the highest reliability level. Based on this reliability level, it can be said that the feedback generated automatically by the recognition engine has a high accuracy level and is comparable to the feedback given by the MFB. A complete list of abbreviations is shown in *Appendix I*.

5.1Limitation

Users in Jawi writing must combine characters to form words, thus they must understand the rules for combining characters. Because this study was limited to learning the fundamentals of Jawi, the engine could only detect Jawi characters if the user wrote them individually. The game was created with ABC, and the application only supports the Android environment, thus iOS users will be unable to play the game. According to internet market statistics [54] over 90% of mobile users in Malaysia are Android users; so, the study can still collect sufficient data from Android users.

6.Conclusion and future work

Based on the results and conclusions made from the study, it can be stated that, overall, the automatic score generated by the recognition engine on the writing accuracy of 16 Jawi characters for Jawi characters writing activities has a high-reliability level. This study's reliability level also concludes that the recognition engine's AFB has a high accuracy level and can be compared to the experts' manual feedback in this study. Therefore, it can be summarised that the Jawi characters recognition engine developed can provide almost similar feedback as human feedback.

This engine can be applied for online Jawi characters recognition by providing feedback on the writing accuracy of Jawi characters written by users. There are 32 basic characters in the Jawi script, 28 of which are similar to Arabic characters. Based on the number of points and positions, these 32 characters are then sorted into 16 groups. This research focused on the recognition of 16 different character groups written by users learning the basics of Jawi. Users must combine and connect these characters to form words at the advanced level of Jawi learning. The relationship between these characters has the potential to change the character's look. Because the number of dots and respective positions may vary, future research into the recognition of Jawi characters in word form will be conducted. The deep learning approach, which is frequently used to classify items based on similar types of attributes [55], is also interesting to explore. This technique could be used to classify or categorise Jawi characters, and the results of deep learning algorithms to recognise Jawi characters can be compared to existing research. Because the method requires a large amount of data, more information from users will be gathered.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Author's contribution statement

Norizan Mat Diah: Conceptualization, manuscript drafting, design, data collection and analysis. **Ratna Zuarni Ramli:** Manuscript drafting, interpretation of results. **Nor Azan Mat Zin and Azizi Abdullah:** Investigation on limitations, supervision, review and editing. All the authors have read and approved the final manuscript.

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Appendix I

S. No.	Abbreviation	Description
1	AFB	Automatic Feedback
2	C-R Splines	Catmull-Rom Spline algorithm
3	DWT	Discrete Wavelet Transform
4	FCC	Freeman Chain Codes algorithm
5	Krippendorff's α	Krippendorff's Alpha
6	MFB	Manual Marking Feedback
7	RS	Recognition Sample