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Optimizing Quranic Literacy with the Tamam Method: Leveraging Artificial Intelligence for Handwritten Arabic Recognition

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Abstract

Indonesia, boasting the world's largest Muslim population, has witnessed a swift augmentation in its Muslim demographic. As of 2020, Muslims in Indonesia numbered 209 million, which surged to 219 million in 2021. Such an observation is alarming, especially given the Quran's centrality in Islamic teachings and the profound link between grasping its tenets and the capability to read and write its verses. This paper introduces an innovative application employing the Tamam method, optimized for enhancing Quranic literacy through the recognition of handwritten Arabic texts using Convolutional Neural Networks (CNN). Involving a cohort of 144 participants, who answered 65 questions, a dataset encompassing 3,842 data points was curated for testing and validation. Preliminary results showcased the model's evolution, with a notable rise in accuracy from 14.27% in the initial epoch to 88.87% in the 20th epoch. Despite such advancements, fluctuations in the validation data hinted at potential overfitting scenarios. This study demonstrates the feasibility of integrating the Tamam method with AI-based handwritten Arabic recognition as a supportive tool for Quranic writing practice. It paves the way for more resilient and adaptive Quranic educational tools, ensuring learners grasp the Holy Text in its true essence.

Keywords: Convolutional Neural Network, Handwritten Analysis, Quranic Literacy, Tamam Method.

INTRODUCTION

Indonesia, as the country with the largest Muslim population in the world, has observed rapid growth in its Muslim populace. In 2020, the number of Muslims in Indonesia reached 209 million and escalated to 219 million in 2021 (Adhiyasa, 2021; Dinas Perhubungan DIY, 2020). Surprisingly, data indicates that over 50% of them are still illiterate in reading the Quran (Ansyari Syahrul, 2018; Junari, 2020; Novita Intan, 2018; Nurulah, 2020; R. Saputra, 2020; W. Saputra, 2020). This poses a deep concern, considering the Quran is the primary source of teachings in Islam, and understanding its content is closely related to one's ability to read and write its verses.

A promising solution to address this issue is the Tamam Method. Introduced for the first time in 1980, this method approaches character writing by adhering to logical rules, simplifying the

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process of Arabic writing (Giftia, 2014). Based on previous research, test results of this method have proven that Tamam is effective in enhancing the ability to write the Quran (Giftia, 2014). However, a gap remains: there is yet to be a digital application that facilitates this method.

The digital age and the prevalence of distance learning demand adaptation. An application for writing the Quran based on the Tamam Method would offer immense benefits for the entire Muslim community. The advantage of technology lies in its flexibility. Writing the Quran can be done by anyone, anywhere, and anytime. Modern systems are capable of recognizing handwriting online. This automatic handwriting recognition is divided into two types, depending on how input is presented to the system. There's an offline approach, where scanned handwriting or path texts, transformed into a digital image format, are fed into the system. On the other hand, there's an online approach, where users compose their text on a digital device (like a digital tablet) using a specific stylus. Digital samples are provided to the system in the form of a sequence of 2D points in real-time (Biadsy, n.d.; Miftahul Amri, 2022).

Various artificial intelligence approaches can be employed according to business needs and desired outcomes, including automatic handwriting recognition. Prior studies have leveraged various algorithms for recognizing handwriting, both online and offline. Examples include the beta-elliptic model and hybrid TDNN-SVM for multi-language writing (Zouari, Boubaker, & Kherallah, 2019), DBLSTM for Arabic writing (Maalej & Kherallah, 2020), Convolutional Neural Networks (Mandal, Prasanna, & Sundaram, 2019), Support Vector Machine (Bahlmann, Haasdonk, & Burkhardt, 2002), RNN for Devanagari scripts (Keshri, Kumar, & Ghosh, 2018), graphemes segmentation and RNN (Hamdi, Boubaker, & Alimi, 2021), Fuzzy perceptual (Akouaydi et al., 2019), and HMM for Arabic writing (AMROUCH, Mouhcine, & EL MEZOUARY, 2019; Amrouch, Rabi, & Es-Saady, 2018). The novelty of this research lies in the modeling of the Arabic writing path based on the Tamam method and the online recognition of handwritten text using Convolutional Neural Networks (CNN).

While previous studies have explored Arabic handwriting recognition using various machine learning approaches, most focus purely on technical accuracy and are detached from structured Quranic learning methods. Conversely, pedagogical approaches such as the Tamam method have proven effective in improving Quranic writing skills but lack digital and intelligent support systems. This study bridges this gap by integrating the Tamam method into an AI-based online handwriting recognition system.

This study aims to evaluate the feasibility and performance of a CNN-based handwritten Arabic recognition system integrated with the Tamam method as a digital support tool for Quranic writing practice. By combining a structured pedagogical approach with artificial intelligence, this research focuses on assessing system performance and real-time feedback capability rather than directly measuring learning outcomes or long-term Quranic literacy improvement.

METHODOLOGY

2.1. Tamam Method

Reading and writing are two fundamental aspects of linguistic capability that are interrelated. Therefore, learning to read must be accompanied by learning to write so that students can understand the subject matter. By making reading and writing the basis of learning, students will be better able to deepen and develop their learning competencies (Titik, Ika, & Wulandari, 2017).

This underpins the Tamam metode of introducing Quranic letters through a combined approach of reading and writing. The objective is for students to recognize and master the writing system, enabling them to read and write using it.

The Tamam method was first published by Drs. H. A. Tata Tamushita in 1982 (Giftia, 2014). "Tamam" is an Arabic term meaning "complete" or "perfect." Within the Tamam method, there are 13 chapters that can be transformed into 13 face-to-face sessions. The materials include:

1. Basics of Quranic reading and writing,
2. Six letters that cannot be connected forward,
3. Dots that form the sounds of five letters,
4. The tail that is cut,
5. The straightened tail parts 1 and 2,
6. Letters combined without alteration,
7. Straightened tail with a triangle in the middle,
8. Combining the letters fa and qaf,
9. The letters Ka Li,
10. The letters Mim Ha,
11. Alif Lam Qamariyah,
12. Alif Lam Shamsiyyah,
13. Rules of the silent nun and tanwin.

2.2. Convolutional Neural Network

Convolutional Neural Networks (CNN) are a category of deep learning models particularly adept at processing grid-like data structures, such as images(Chauhan, Ghanshala, & Joshi, 2018; Chua, 1998; Heryadi & Irwansyah, 2020; LeCun, Bottou, Bengio, & Haffner, 1998; Saha, 2018; Wu, 2017). This unique capability is due to their architectural design, which includes convolutional layers that automatically and adaptively learn spatial hierarchies of features from input images. CNNs are known for reducing the number of parameters, preventing overfitting, and being particularly efficient for tasks like image classification, making them a prime choice for online handwritten text recognition.

The CNN architecture consists of convolutional layers for feature extraction followed by fully connected layers for classification. The model was trained using supervised learning with categorical cross-entropy loss and optimized using Adam optimizer. CNN was selected due to its effectiveness in spatial feature extraction from image-based handwriting data and its relatively lower computational complexity compared to sequence-based models.

In this study, CNNs will be deployed for the online reading of handwritten text, providing instantaneous feedback on whether the recognized text is correct or incorrect. Users will be tasked with 65 questions, challenging them to connect letters into sequences of words in Arabic, aligned with the Tamam method. The immediate response mechanism will not only enhance the user experience but also expedite the learning process by allowing users to instantly rectify their mistakes and reinforce correct practices.

RESULTS AND DISCUSSION

The dataset used in this study consists of two levels of data collection. An initial dataset of 350 base handwritten image samples was prepared to support early system development. During system deployment and user testing, 144 users completed 65 writing tasks, producing a total of 3,842 handwritten image samples. These samples were used for training and validation to evaluate the performance of the proposed CNN-based recognition model.

The image showcases on Figure. 1 is the interface of "Tamam," an educational platform focusing on the Tamam method for learning and writing the letters of the Al-Quran. Differing from Latin writing techniques, the Tamam method adopts an approach that hinges on similarities between the Arabic script's letters, making it easier for learners to grasp and remember. The platform emphasizes the practice of writing in Al-Quran, incorporating distinct task units that facilitate the comprehension of the material and exercises. It is also designed to immediately read the user's input and provide feedback if there's an error. The main navigation includes options such as "Home," "Learning Module," "Leader Board," and "About Us." A central "Let's Play" button prompts the user to engage with the application. Additional information highlights that 144 users have tested the application, there are 65 questions available, and there have been 3842 answers provided. The application's interface is adorned with a character illustration depicting a child reading, emphasizing the platform's educational purpose. For direct access, the Al-Quran handwriting application using the Tamam method is available at: https://tamam.informatika.digital. The quiz mode is shown in the Figure 2.

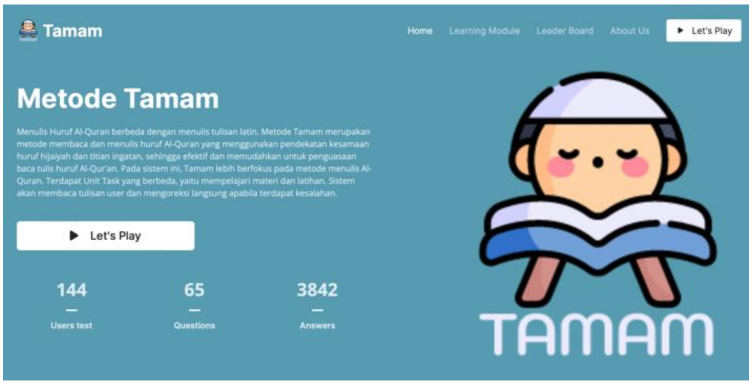

Figure 1. Tamam home interface

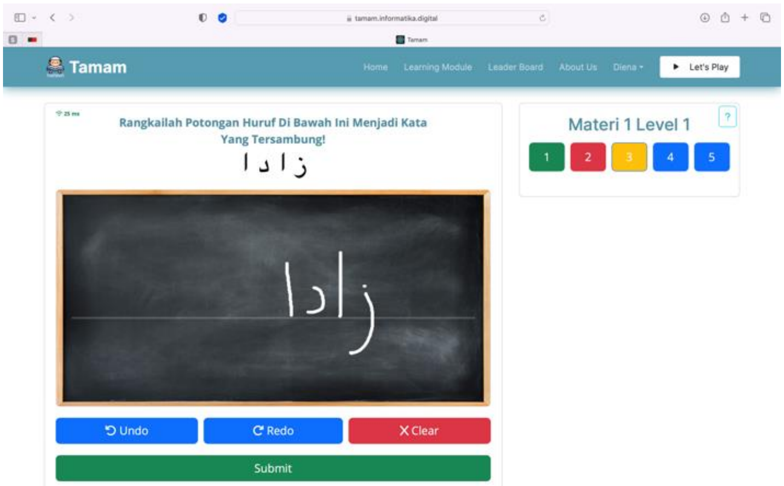

Figure 2. Quiz mode interface

In the use case shown in Figure. 3, three primary entities are depicted: Actor, Expert, and Admin, each having specific roles and interactions with the system. The Actor, who might be a student or user, can register in the application, log in, view rankings on the leaderboard, and save their learning progress. Meanwhile, the Expert, who is a teacher or specialist in the Tamam method, has the capability to add new questions, confirm the training dataset, and save it. The admin, managing the technical and administrative aspects of the application, is responsible for creating accounts for the Experts. Consequently, this application is designed to support the learning and writing process of the Quran using the Tamam approach, ensuring the quality of materials presented through contributions from the Experts.

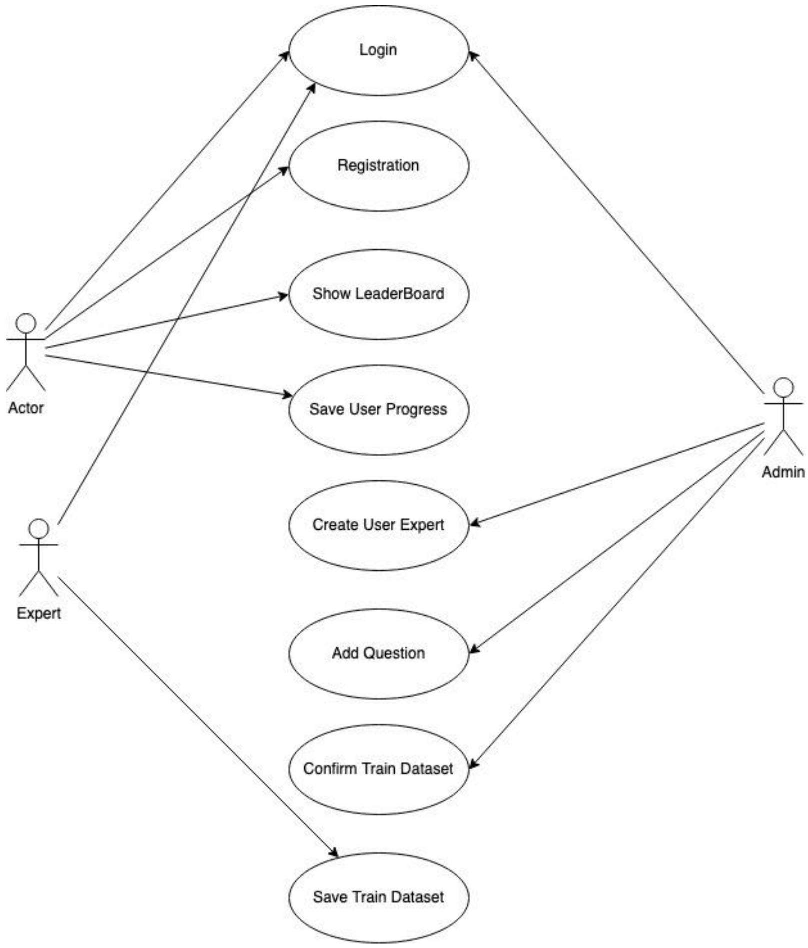

Figure 3. Use case diagram

The data collection process involves a collection of handwritten images in Arabic. Each image represents a segment of a word or phrase in Arabic. From the visualization provided, there is a variation in writing styles, which might indicate that the writings come from several different authors. This diversity is essential to ensure diversity in the dataset, which will enhance the reliability and generalization of the training model, especially if the goal is handwritten recognition. The total data collected amounts to 350 image data as shown in Figure.4.

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"Skeletonization" is a digital image processing technique used to reduce dark-colored objects (in this case, handwriting) into thin line forms without altering the original topology of the object. The purpose of this process is to obtain the basic structure of an object by eliminating redundant parts.

In Figure. 5, the skeletonization process has been applied to handwritten Arabic text. It can be seen from how the writing, which might have originally had a certain thickness, has now been reduced to thin lines. Even though it has been transformed into thin lines, the original shape of the writing remains recognizable.

The dataset used in this study consists of two levels of data collection. An initial dataset of 350 base handwritten image samples was prepared to support early system development. During system deployment and user testing, 144 users completed 65 writing tasks, producing a total of 3,842 handwritten image samples. These samples were used for training and validation to evaluate the performance of the proposed CNN-based recognition model.

Testing of the CNN algorithm was conducted by examining Arabic handwriting data input by users. A total of 144 users participated in the testing by completing 65 items connecting Arabic letters. This produced 3,842 image data from the users' answers. This data was then tested for its accuracy level and divided into 20 training and test data, as shown in tables 1 and 2.

Figure 4. Data Collection Process

Table 1. Training Data Test Results

Epoch	Loss	Accuracy
1	3.6011	14.27%
2	2.4632	37.03%
3	1.8605	51.69%
4	1.5333	58.63%
5	1.3198	65.20%
6	1.1494	69.07%
7	1.0153	73.06%
8	0.9299	74.98%
9	0.8096	77.86%
10	0.7328	79.89%
11	0.6380	82.69%
12	0.6209	81.89%
13	0.5950	82.58%
14	0.5316	84.92%
15	0.5336	84.77%
16	0.4619	86.80%
17	0.4574	87.34%
18	0.4042	88.72%
19	0.3780	88.18%
20	0.3637	88.87%

The training data presented in Table 1 reflects the progression of a model over 20 training epochs. The "Epoch" denotes the training rounds, with each row signifying one complete cycle through the dataset, totaling 20 rounds. The "Loss" metric indicates the model's predictive capability during training; a lower loss value signifies better prediction. Notably, there was a significant reduction from 3.6011 in the first epoch to 0.3637 in the 20th epoch, indicating model performance improvement. The "Accuracy" metric demonstrates the percentage of correct predictions by the model against the training data. An uptick from 14.27% in the initial epoch to 88.87% in the final one showcases the model's enhanced data classification capabilities. In essence, the model showed significant performance enhancement throughout the training process, evolving from low accuracy and high loss to markedly improved accuracy and diminished loss over time.

Although the training accuracy shows a consistent upward trend, fluctuations observed in the validation accuracy and validation loss suggest early signs of overfitting. This behaviour is common in handwriting recognition tasks involving diverse writing styles and limited datasets. Nevertheless, the achieved validation accuracy indicates that the model is sufficiently robust for real-time educational feedback, where the primary objective is to support learners in practicing correct writing patterns rather than achieving perfect character recognition.

Table 2. Validation Data Test Result

Epoch	Val_Loss	Val_Accuracy
1	2.2400	38.28%
2	1.4547	61.72%
3	1.2473	64.83%
4	1.0647	69.66%
5	0.9477	74.48%

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Epoch	Val_Loss	Val_Accuracy
6	0.8569	76.90%
7	0.9133	75.52%
8	0.7408	79.31%
9	0.7457	80.00%
10	0.7274	80.00%
11	0.7326	81.03%
12	0.7398	82.07%
13	0.6795	81.38%
14	0.6164	85.17%
15	0.6088	85.17%
16	0.5748	84.14%
17	0.6282	84.14%
18	0.6002	86.21%
19	0.6982	82.41%
20	0.6688	83.45%

The validation Table 2 showcases the model's performance on unseen data (validation data) over 20 training epochs. The "Epoch" section signifies the training rounds, with every row representing one complete training cycle across the dataset, confirming that the model underwent 20 training iterations. The "Val Loss" metric reveals the model's predictive efficacy on validation data, and a decline is observed from 2.2400 in the inaugural epoch to 0.6688 in the 20th, though some epochs experienced slight increases. The "Val Accuracy" metric displays the model's precision percentage on the validation data, noting an ascent from 38.28% initially to 83.45% in the end, albeit with intermittent fluctuations. In conclusion, the validation data indicates the model's substantial performance augmentation throughout the training phase. However, sporadic fluctuations in Val Loss and Val Accuracy across certain epochs may hint at potential overfitting or other training challenges. Overfitting arises when a model overly adapts to training data, compromising its generalizability on unfamiliar data, underscoring the importance of consistently monitoring model performance on validation data to ensure optimal generalization.

Based on the provided training and validation data tables, several key conclusions can be drawn. First, in terms of training progress, the model exhibited significant improvements throughout the process. Within the training data, the model's accuracy rose from 14.27% in the first epoch to 88.87% in the 20th epoch, indicating effective learning from the data. Second, in performance on validation data, despite some fluctuations, the model generally displayed positive advancements, with accuracy increasing from 38.28% to 83.45% by the 20th epoch, showcasing the model's ability to generalize learning. Third, fluctuations in Val Loss and Val Accuracy during certain epochs need attention, potentially hinting at overfitting towards the training data, leading to less stable performance on validation data. Lastly, overfitting remains a crucial consideration, especially when the model demonstrates significant performance disparities between training and validation data or undergoes fluctuations in validation data. In conclusion, although the model has shown good progress, it's essential to monitor potential overfitting and contemplate specific techniques, such as dropout, regularization, or data augmentation. Additionally, implementing strategies like early stopping when the model starts indicating signs of overfitting could be a prudent step.

Although the training accuracy shows a consistent upward trend, the observed fluctuations in validation performance suggest early signs of overfitting. This behavior is common in handwriting recognition tasks involving diverse writing styles and limited datasets. Nevertheless, the achieved validation accuracy indicates that the model is sufficiently robust for real-time educational feedback, where the primary objective is to support learners in practicing correct Quranic writing patterns rather than achieving perfect character recognition. These results suggest that the proposed system is suitable as a supportive learning tool, while also highlighting the need for further optimization through dataset expansion and regularization strategies in future work.

CONCLUSION

This study presents an AI-assisted Quranic handwriting application that integrates the Tamam method with a CNN-based handwritten Arabic recognition system. Experimental results demonstrate that the proposed model can recognize handwritten Arabic script with promising accuracy and can provide real-time feedback to support Quranic writing practice. While the system shows strong technical performance, this study focuses on system feasibility and recognition accuracy rather than directly measuring learning outcomes or long-term improvements in Quranic literacy. Future work should expand the dataset, explore alternative neural network architectures, and conduct longitudinal user studies to evaluate the educational impact of the system more comprehensively.

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