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Comparative Optimization of Tajwid Detection in Quranic Verses Using Deep Learning

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ABSTRACT

This study addresses the challenge of accurate Qur'anic recitation, particularly the rules of nun sakinah and tanwin, which are often difficult for learners to master through traditional instruction. The research aims to develop and evaluate an automated tajwid detection system using a deep learning–based object detection model to assist learners in accurately and interactively recognizing tajwid rules. The method involved dataset preparation from 125 Qur'anic pages, producing 600 annotated instances across five tajwid classes. The dataset was preprocessed and divided into training, validation, and test sets. Model performance was evaluated using precision, recall, and mean Average Precision. The system was deployed in a web-based interface that supports both image upload and real-time camera detection. The results showed an overall accuracy of 94.6%, with a precision of 96.5% and a recall of 90.2%. The findings indicate that the Smart Tajwid system effectively integrates deep learning and educational technology to support Qur'anic learning.

Keywords: *Artificial Intelligence, Computer Vision, Deep Learning, Qur'an, Tajwid Detection*

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INTRODUCTION

The Al-Qur'an is the holy book of Muslims, revealed as guidance for humanity. Its recitation is not only a ritual practice but also a linguistic responsibility that must follow the rules of tajwid to ensure the preservation of meaning (Tarshany & Zeki, 2024). Tajwid governs the correct articulation of each letter so that no semantic distortion occurs during recitation. Errors in reciting the Qur'an may result in significant changes in meaning, making mastery of tajwid essential for every Muslim (Engkizar et al., 2025). Surah Al-Fatiha, for instance, occupies a central role in prayer and requires precise pronunciation. While learning tajwid is categorized as fardu kifayah, reciting the Qur'an with proper tajwid is considered fardu 'ain for all Muslims (Ariani & Realita, 2020). This obligation is reinforced by the command in Surah Al-Muzammil [73:4] to recite the Qur'an "in measured rhythmic tones."

One of the key components in tajwid is the correct reading of nun sakinah and tanwin. These rules apply when nun sakinah or tanwin encounters specific Arabic letters, resulting in four main categories: Izhar, Idgham, Iqlab, and Ikhfa (Ellyadi, 2022; Prayitna et al., 2022). Each rule requires different articulatory patterns, reflecting the precision needed in tajwid (Noor & Ariffin, 2020). For beginners or non-native Arabic speakers, however, memorizing and applying these rules can be challenging and sometimes overwhelming (Zulkifli & Jamal, 2021).

Advancements in digital technology offer new opportunities to support accurate Qur'anic recitation. Artificial intelligence (AI), particularly deep learning, has demonstrated strong capabilities in automating image-based analysis (Kulkarni et al., 2025). Among the leading algorithms is You Only Look Once (YOLO), which delivers high accuracy in real-time object detection (Alqahtani, 2022). The latest version, YOLOv8, is capable of recognizing detailed visual patterns and is therefore suitable for identifying diacritical marks and contextual letter arrangements that reflect tajwid rules (Padilah et al., 2023).

Several prior studies have explored computer vision applications in Islamic education. Hamdhana et al. (2018, 2022) developed tajwid detection systems using Euclidean and Bray–Curtis distance methods, achieving detection rates of 70–90% but with high false positives. Padilah et al. (2024) implemented YOLOv8 for detecting nun sakinah, achieving 91.7% accuracy, with rule-specific performance varying—high for Idgham bilaghunnah (95.5%) and lower for Iqlab (84.5%). These findings highlight both the potential and the remaining challenges in automated tajwid detection (Akhtar & Khalid, 2022).

The core research problem addressed in this study stems from the gap between the need for accurate tajwid recitation and the limitations of traditional teaching methods. Tajwid instruction typically relies on direct teacher-student interaction, which varies in quality and does not scale efficiently. Students often struggle with memorization and fail to consistently apply the rules of nun sakinah and tanwin. This situation underscores the need for automated tools capable of providing real-time guidance and objective feedback.

To address this issue, the present study proposes using YOLOv8 to detect and classify tajwid rules, with a focus on nun sakinah and tanwin. The research seeks to answer two main questions: (1) How can YOLOv8 be effectively implemented to detect tajwid rules in Qur'anic text images? and (2) How accurate is YOLOv8 in identifying nun sakinah and tanwin compared with existing benchmarks? Through systematic development and evaluation, this study aims to produce an AI-based educational tool that is both practical and reliable.

Theoretically, this research sits at the intersection of deep learning, linguistics, and Islamic pedagogy. Deep learning, with its multilayered neural structures, is capable of automatically extracting visual features from images (Nugroho et al., 2020). Computer vision methods further provide the basis for interpreting text-like patterns (Prayitna et al., 2022). This interdisciplinary framework supports the application of YOLOv8 to tajwid analysis.

The significance of this study lies in advancing AI applications in religious education and promoting accurate Qur'anic recitation. For learners, the system provides consistent and personalized feedback, reducing dependency on memorization and enhancing confidence. For teachers, it serves as an auxiliary assessment tool, offering objective evaluations of student performance. Additionally, it supports broader initiatives in digital Islamic education by preserving traditional values while embracing modern technology.

In summary, this study has two main objectives: (1) to implement the YOLOv8 model for analyzing nun sakinah and tanwin in the Qur'an and (2) to evaluate the accuracy of the detection system in identifying these rules. The expected contributions include theoretical insights into the integration of AI and Islamic studies, as well as practical benefits for learners, teachers, and the wider Muslim community.

The main contribution of this study lies in the development of a YOLOv8-based model for identifying nun sakinah and tanwin in Qur'anic text images, supported by a curated dataset of annotated tajwid features. The study also provides a comprehensive performance evaluation of the model and proposes an AI-assisted learning tool designed to support accurate Qur'anic recitation.

METHOD

This study adopted a systematic research framework designed to ensure the accuracy and reproducibility of the results (Mahmud et al., 2024; Mulyana & Rowis, 2022). The research began by identifying the problem and defining the study boundaries, followed by an extensive literature review that contextualized the work's focus. Classical tajwid references such as Tuhfatul Athfal were consulted to establish a linguistic foundation, while prior studies on computer vision and object detection informed the selection of YOLOv8 and the use of transfer learning for model optimization (Jocher & Ultralytics Team, 2023; Bochkovskiy et al., 2020).

1. Data Collection and Annotation

Primary data were obtained from photographs of Qur'anic pages covering Surah Al-Fatiha through Al-A'raf. A total of 125 pages were collected between 15 April and 5 May 2025. All source images were taken from publicly available and legally distributable digital mushaf copies without any modification to ensure the integrity and sanctity of the Qur'anic script. The collection process resulted in 600 annotated instances across five tajwid rules: Idgham Bighunnah (161), Idgham Bilaghunnah (60), Ikhfa (215), Iqlab (23), and Izhar Halqi (141). Annotation was performed using Roboflow with bounding boxes and subsequently verified against authoritative tajwid references to ensure linguistic correctness. The complete distribution of annotated data is presented in Table 1.

Table 1: Annotated data distribution

Code	Indicator	Count
0	Idgham Bighunnah	161
1	*Idgham Bilaghunnah*	60
2	Ikhfa	215
3	Iqlab	23
4	Izhar Halqi	141

The data collection process was carried out over three weeks, between April 15 and May 5, 2025. During the first week, 63 pages were collected, followed by 62 pages in the second week. Each image was cropped and normalized to a resolution of 640 × 640 pixels before being uploaded into Roboflow. Annotation was verified by cross-checking with *tajwid* references to ensure that each visual feature aligned with the linguistic rules of Qur'anic recitation (Mulyana & Rowis, 2022). The timeline of data collection is summarized in Table 2.

Table 2: Data collection timeline

Week	Date Range	Activity
1	15–21 April 2025	Collection of 63 Qur'an pages
2	22–28 April 2025	Collection of 62 Qur'an pages

2. Preprocessing and Data Augmentation

Each image was cropped and normalized to a resolution of 640 × 640 pixels. To improve generalization and reduce overfitting caused by the relatively small dataset, several data augmentation techniques were used, including slight rotations (±5°), brightness adjustments (±10%), horizontal flips, and minor affine transformations. These augmentations keep the structural features of the Qur'anic script intact while adding controlled variability.

3. Dataset Partitioning and Validation Strategy

The dataset was divided into 87 training images (300 annotations), 25 validation images (200 annotations), and 13 test images (100 annotations). A stratified split approach was adopted to maintain proportional representation of each tajwid class across the three subsets. Pages originating from the same Qur'anic source were kept within the same partition to prevent data leakage and ensure a fair evaluation of model performance.

4. Model Training

Model training was conducted using YOLOv8, with comparative experiments performed against YOLOv5 to assess performance differences. Training was implemented in Python 3.10.7 within a Flask 3.0.0 environment and supported by Ultralytics, OpenCV, NumPy, and Pillow libraries. The hardware environment consisted of a Lenovo Ideapad Slim 3 equipped with an Intel Core i3 processor, 8 GB RAM, and 512 GB SSD storage. Due to limited GPU capability, training was performed using small batch sizes and longer epochs to accommodate computational constraints.

5. System Architecture

The system architecture begins with user-uploaded Qur'anic images, which undergo preprocessing before being analyzed by the YOLOv8 detection model. The model outputs bounding boxes indicating the location and type of tajwid rule, along with confidence scores. The workflow diagram is illustrated in Figure 1.

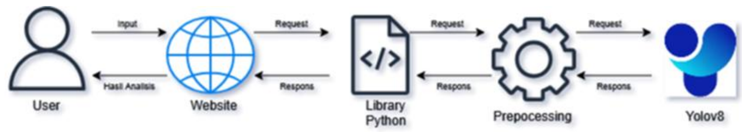

Figure 1: System architecture for *tajwid* detection

6. Evaluation Metrics

Model performance was evaluated using three standard metrics in computer vision: precision, recall, and mean Average Precision (mAP). These metrics provide a comprehensive assessment of detection accuracy and reliability, particularly for multi-class object recognition tasks (Padilla et al., 2021). The test dataset was used to compare YOLOv8 and YOLOv5 performance under identical conditions.

The methodological design is expected to produce a robust YOLOv8-based detection model capable of identifying tajwid rules with high accuracy while demonstrating clear advantages over YOLOv5. The final model is integrated into a web-based interface to support ease of use and promote independent tajwid learning within the community.

RESEARCH RESULT

1. System Implementation Results

The implementation of the Smart Tajwid system demonstrates the integration of artificial intelligence (AI), computer vision, and natural language processing into an interactive platform designed for learning Tajwid. The system provides separate interfaces for two primary user roles: the general user and the administrator. The user interface focuses on analysis functionalities, while the administrator interface enables dataset management, training, and testing of the tajwid detection model. The Home page serves as the primary entry point for users into the Smart Tajwid system. Positioned at the top of the interface is a navigation bar containing four main menu home, about, feature, and a special sign-in button for administrator login. The page also provides two key functionalities: camera access and image upload, both essential for initiating tajwid analysis. Figure 2 illustrates the design of the Home page.

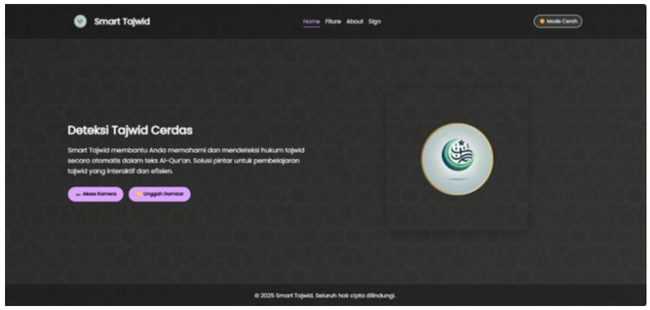

Figure 2: Home page of Smart *Tajwid* system

The About page provides introductory information regarding the platform, including its objectives, benefits, and available contact channels for technical support. This section emphasizes the system's role as an innovative platform leveraging OCR and machine learning to facilitate interactive tajwid learning. Figure 3 presents the interface of the About page.

Figure 3: About page of Smart *Tajwid* system

The Feature page is designed as the core functional space for tajwid analysis. Users are offered two methods of analysis: real-time detection through a webcam and static detection through image uploads. The real-time detection integrates video streaming with bounding box annotations, while the upload option processes static images with visual and quantitative feedback. Figure 4 demonstrates the interface of the Feature page.

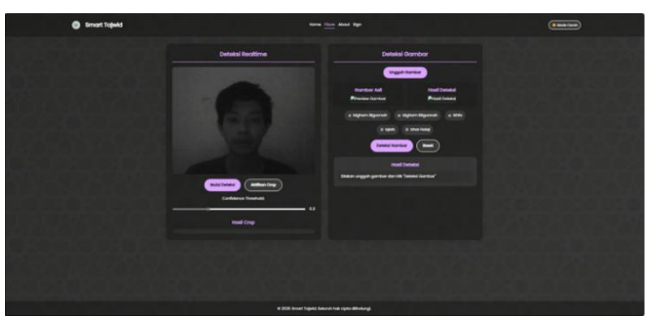

Figure 4: Feature page of Smart *Tajwid* system

The upload functionality enables users to analyze tajwid rules through static images. After image submission, the system processes the input and generates a side-by-side visualization between the original image and the annotated output. The annotated image highlights detected objects, while quantitative results present the count of each detected tajwid rule. Figure 5 depicts the Upload Image Analysis interface.

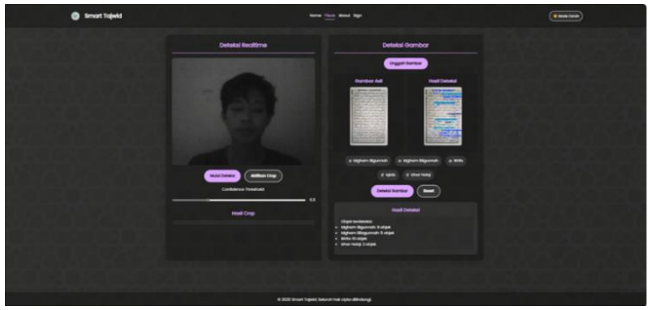

Figure 5: Image Upload Analysis Result

The real-time detection page allows direct streaming from a webcam to identify tajwid objects instantly. The annotated video feed highlights bounding boxes, while cropped detection segments are presented below for more detailed inspection. Figures 6 and 7 showcase the results of real-time analysis and cropped detection, respectively.

Figure 6: Real-Time Camera Analysis

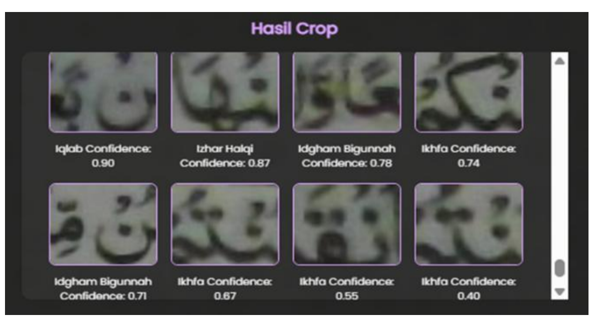

Figure 7: Cropped Detection Result from Real-Time Camera

The administrator interface includes essential functions such as login, data management, training, and testing of the detection model. The login page provides secure access to these functionalities. The login page functions as the access gateway for administrators. Through this portal, administrators can log in securely to manage datasets, train the detection model, and evaluate testing outcomes. Figure 8 shows the administrator login page.

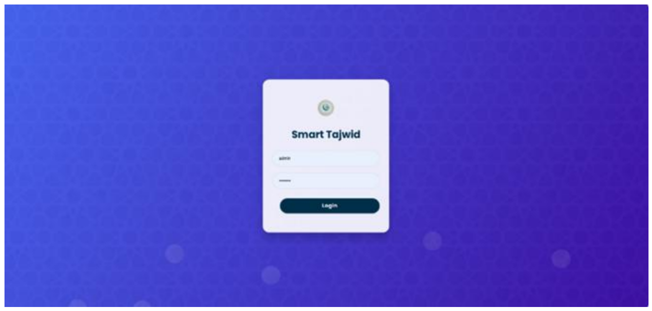

Figure 8: Administrator Login Page

The Data Management page provides functionalities to upload datasets and monitor annotation progress. Upon successful upload, the system displays the number of annotated images and generates bar chart visualizations to represent the distribution of tajwid classes. Figures 9 and 10 present the Data Management page and bar chart visualization, respectively.

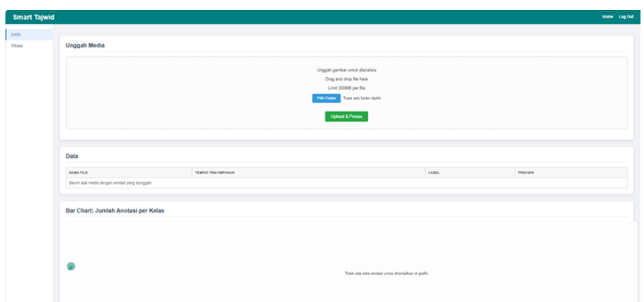

Figure 9: Data Management Page

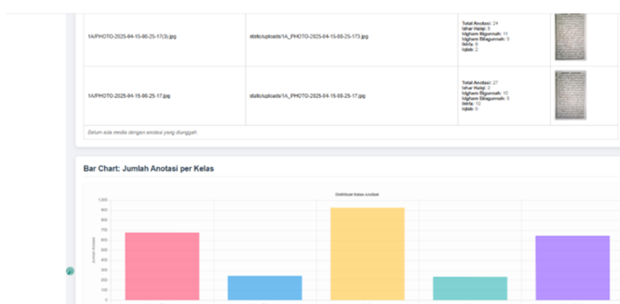

Figure 10: Bar Chart of Annotation Counts

The Training page serves as the central control interface for model training. Administrators can configure key parameters such as the number of epochs, image size, batch size, learning rate, and data splitting ratio. Once initiated, the system automatically displays training performance metrics, including Results, Precision Confidence Curve, Recall Confidence Curve, and F1 Confidence Curve.

The Testing page enables administrators to evaluate the performance of the trained model using test datasets. Results are presented comprehensively with quantitative metrics including total test data, precision, recall, mAP50, and mAP50-95. Figure 11 shows the testing page interface.

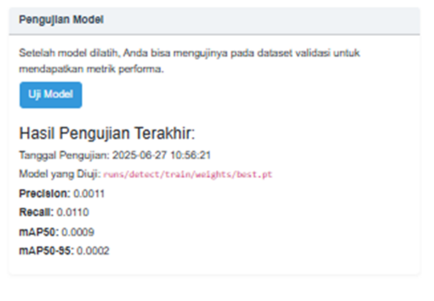

Figure 11: Testing Page of Smart Tajwid System

2. Model Evaluation

The confusion matrix in Figure 12 below illustrates the classification performance of the YOLO-based tajwid detection model across six categories: Idgham Bigunnah, Idgham Bilagunnah, Ikhfa, Iqlab, Izhar Halqi, and background. The diagonal elements demonstrate that the model correctly predicts the majority of samples in each class, indicating strong class-level discrimination.

Among all categories, Ikhfa exhibits the highest number of true positive predictions (215), followed by Idgham Bigunnah (161) and Izhar Halqi (141), reflecting the model's robust capability to identify these tajwid rules accurately. Misclassifications are relatively limited and primarily occur between phonetically or visually similar classes, such as occasional confusion between Idgham Bilagunnah and Ikhfa, or between Ikhfa and background. These errors remain minor compared to the overall sample sizes.

Overall, the confusion matrix supports the quantitative evaluation metrics reported earlier, confirming that the model achieves high accuracy, precision, and recall, with minimal cross-class confusion.

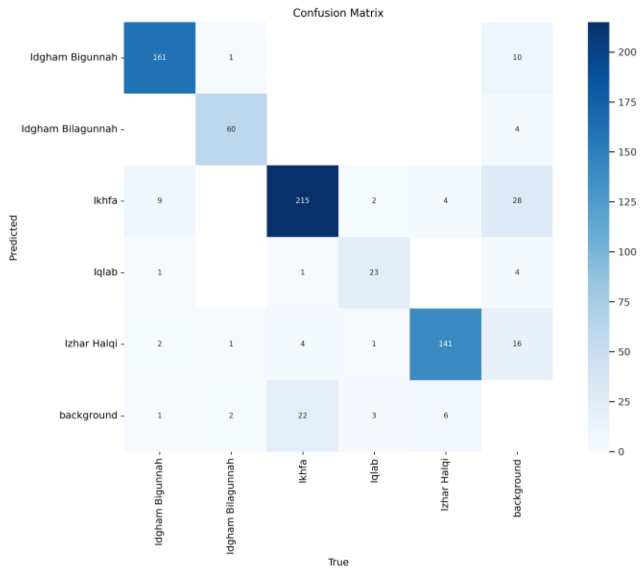

Figure 12. Confusion Matrix

Figure 13 below presents the F1-confidence curves for all tajwid classes, illustrating how the model's F1-score varies across different confidence thresholds. The curves show that the model maintains high F1 performance over a broad confidence range, with optimal values occurring between approximately 0.2 and 0.6. Idgham Bilagunnah and Idgham Bigunnah achieve the highest peak F1-scores, indicating a strong balance between precision and recall for these classes. Meanwhile, Ikhfa, Iqlab, and Izhar Halqi also demonstrate stable performance, though with slightly lower peak F1 values.

The bold blue curve represents the aggregated performance across all classes, yielding a maximum F1-score of 0.91 at a confidence threshold of 0.333. This suggests that the model achieves its best overall trade-off between precision and recall at this threshold, making it a suitable candidate for deployment or real-time inference settings. The gradual decline in F1-scores at higher confidence values reflects increasing false negatives, whereas very low confidence values lead to more false positives.

Overall, the F1-confidence analysis confirms the robustness of the proposed YOLO-based tajwid recognition model and highlights the optimal threshold for achieving balanced classification performance across all classes.

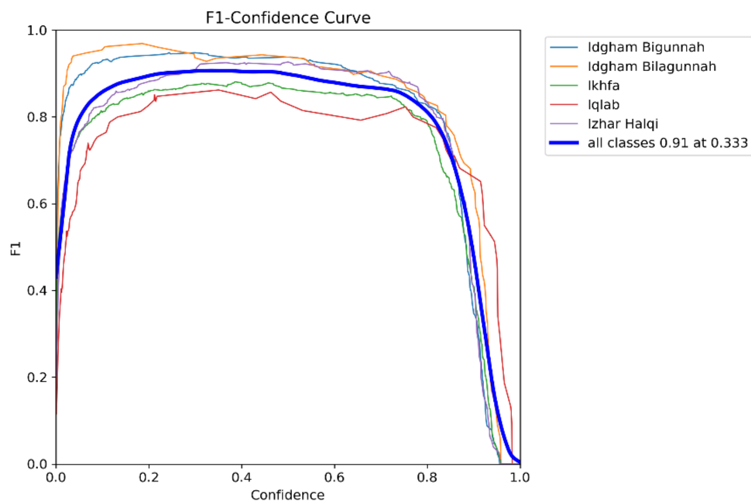

Figure 13. F1-Confidence Curves

The precision–recall curves presented in Figure 14 below illustrate the model's ability to maintain high precision across varying recall thresholds for each tajwid class. The results demonstrate consistently strong performance, with all classes achieving high average precision values. *Idgham Bilagunnah* attains the highest AP score (0.987), followed by *Idgham Bigunnah* (0.971) and *Izhar Halqi* (0.953). The *Ikhfa* and *Iqlab* classes also perform well, with AP scores of 0.911 and 0.908, respectively.

The aggregated curve representing all classes (shown in bold blue) yields a mean Average Precision (mAP@0.5) of 0.946, indicating robust overall model performance. The steep and sustained precision values across the recall range further confirm that the model can accurately detect tajwid features while minimizing false positives, even under increasing recall conditions. Overall, the precision–recall analysis supports the reliability and generalization capability of the proposed YOLO-based tajwid detection system.

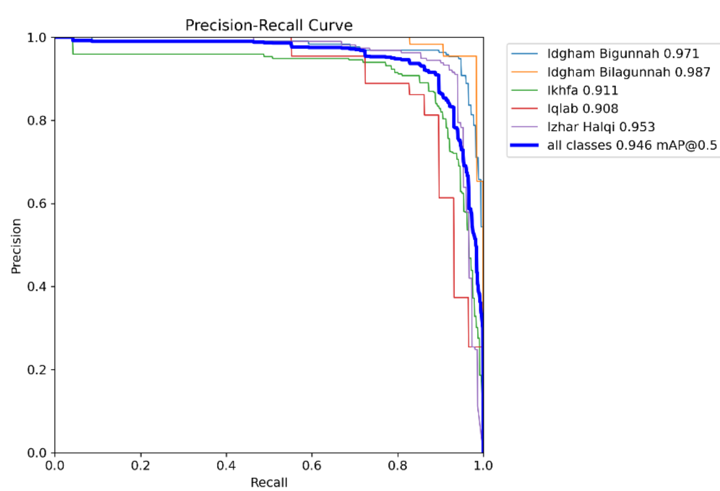

Figure 14. Precision-Recall Curves

Figure 15 below presents the training and validation curves for the YOLO-based tajwid recognition model over 100 epochs. The first row illustrates the training losses—including box loss, classification loss, and distribution focal loss—each demonstrating a consistent downward trend. This steady decrease indicates that the model progressively improved its ability to localize bounding boxes and classify tajwid categories with higher accuracy throughout the training process.

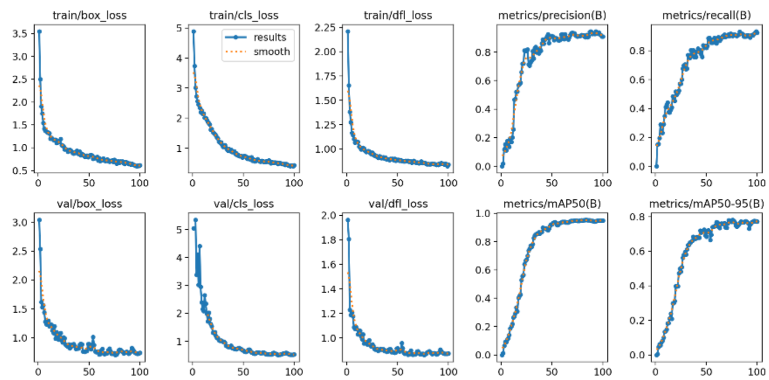

Figure 15. Training and Validation Loss Curves

Similarly, the second row shows the corresponding validation losses, which also decrease over time and stabilize in the later epochs. The close alignment between training and validation curves suggests that the model generalizes well and does not exhibit signs of overfitting.

The rightmost columns in both rows display the evolution of key performance metrics: precision, recall, mAP@0.5, and mAP@0.5-0.95. These metrics steadily increase during training, with mAP@0.5 approaching 0.95 and mAP@0.5–0.95 reaching approximately 0.78, indicating strong overall detection performance. The upward trajectory of precision and recall curves further confirms the model's ability to accurately detect tajwid features with increasing confidence.

Overall, the loss and metric curves collectively demonstrate stable convergence and robust performance, supporting the reliability of the proposed tajwid detection framework.

3. Model Performance Results

Model evaluation was conducted using precision, recall, and mean Average Precision (mAP) on the test dataset. Several train–test data splits (50:50, 60:40, 70:30, 80:20, and 90:10) were used to assess performance consistency. Table 3 presents the quantitative results.

Table 3: Model Performance Metrics on Test Dataset

No	Train: Test Data Ratio	Training Data			Test Data		
		Precision	Recall	mAP50	Precision	Recall	MAP50
1	50:50	74.56%	55.30%	59%	75.2%	55%	60%
2	60:40	74.60%	54.73%	60%	72.13%	53.44%	58.80%
3	70:30	96.5%	90.2%	94.6%	92%	92.52%	96%
4	80:20	70%	52%	54.43%	69%	52.2%	55%
5	90:10	68.76%	51.70%	54.43%	67.74%	51.91%	54.43%

This implementation confirms that the Smart Tajwid system successfully integrates advanced computer vision techniques with a user-friendly web interface. The system not only supports learners in analyzing *tajwid* rules interactively but also provides administrators with robust tools to maintain, train, and improve the detection model.

DISCUSSION

The implementation and evaluation of the Smart Tajwid system demonstrate strong performance in detecting and analyzing nun sakinah and tanwin rules using YOLOv8. The model achieved an overall accuracy of 94.6%, with a precision of 96.5% and a recall of 90.2%, indicating a high degree of reliability in identifying tajwid-related visual patterns. These findings are consistent with previous studies reporting the effectiveness of YOLO-based architectures in recognizing small, dense, and script-specific objects (Gupta et al., 2025; Verma, 2025). The strong performance is further supported by preprocessing strategies—such as normalization and data augmentation, which improved feature extraction and generalization (Haq et al., 2025).

Despite the overall satisfactory performance, accuracy varied across tajwid categories. Idgham Bilaghunnah yielded the highest accuracy (98.7%), whereas Iqlab exhibited the lowest (91.1%). This discrepancy primarily reflects dataset imbalance, as Iqlab had only 23 training examples compared to 215 instances of Ikhfa. Limited representation of minority classes reduces the model's ability to learn their unique morphological patterns, a challenge commonly noted in imbalanced classification problems (Sapkota et al., 2025). Addressing this issue requires dataset rebalancing through expanded annotation, augmentation techniques tailored to Arabic scripts, and the potential use of synthetic data generation (Benkirat, 2023) to improve consistency across classes.

Model behavior across training configurations further highlights the risk of overfitting. Performance peaked at 70 epochs with 95.1% accuracy but declined slightly to 94.6% at 100 epochs. This downward trend suggests that prolonged training reduced generalization capability. Techniques such as early stopping, weight decay, or dropout-based regularization may help stabilize learning and prevent performance degradation at higher epoch counts.

From a functional standpoint, the web-based interface effectively supports both image upload and real-time camera detection. The upload feature provides clear visual feedback by presenting annotated outputs alongside original images, while the real-time module enables immediate detection via webcam. However, performance in the real-time mode is influenced by hardware specifications. Users with lower-end devices may experience reduced frame rates or slower inference times. Implementing lightweight model variants—such as YOLOv8n or YOLOv8s may improve system responsiveness and broaden accessibility across a wider range of devices.

Beyond technical performance, the system also carries important pedagogical implications for Qur'anic learning. By offering automated, immediate feedback on tajwid errors, the Smart Tajwid system can support self-paced learning for beginners and enhance teaching efficiency in formal settings. Teachers may use the tool to rapidly assess students' recitations, while learners can benefit from visual cues and consistent reinforcement of tajwid rules. Such integration of AI-driven analysis has the potential to complement traditional instruction and make tajwid learning more accessible, especially for individuals without regular access to qualified instructors.

Overall, the Smart Tajwid system successfully integrates deep learning–based detection with an intuitive user interface, offering meaningful support for both educational and practical applications. Nevertheless, further work is needed to improve minority class detection and enhance long-term applicability. Expanding annotated datasets, adopting transfer learning using larger Arabic text corpora, and incorporating explainable AI methods such as visual heatmaps to indicate regions influencing prediction could strengthen model transparency and instructional value. By addressing these enhancements, the system can progress toward becoming a more accurate, equitable, and pedagogically impactful tool for tajwid education.

CONCLUSION

This study successfully demonstrates the application of the YOLOv8 model for detecting the tajwid rules of nun sakinah and tanwin in Qur'anic text images. The system achieves high overall performance and provides an accessible platform through its integrated web-based interface, allowing users to conduct real-time detection and static image analysis. These results confirm that computer vision techniques can support tajwid learning by offering consistent and automated visual feedback.

Despite its effectiveness, the system shows performance disparities across tajwid classes, particularly for Iqlab, due to the limited and imbalanced dataset. This limitation affects the model's ability to generalize minority classes and leads to reduced detection consistency. The real-time feature is also influenced by hardware constraints, impacting responsiveness on lower-end devices.

Future development should address these limitations by expanding and balancing the dataset, incorporating digital mushaf sources, and integrating explainable-AI components to provide clearer instructional feedback. Enhancements such as user-history tracking, adaptive learning features, and model optimization using lightweight variants are recommended to increase system scalability and pedagogical impact.

Overall, this research contributes to the advancement of AI-based Qur'anic learning tools and provides a strong foundation for further integration of deep learning technologies into tajwid education within digital environments.

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