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https://doi.org/10.5109/7395645

出版情報：Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 11, pp.1073-1079, 2025-10-30. International Exchange and Innovation Conference on Engineering & Sciences
バージョン：

A Preliminary Study on New Crescent Moon Detection Using "You Only Look Once" (YOLO)

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Abstract: *Accurately determining the start of each lunar month is essential for practicing key Islamic customs, including fasting, Eid celebrations and the Hajj pilgrimage. This study utilized a prototyping process to develop an object detection model that identifies the new crescent moon using computer vision techniques. The International Crescent Observation Project (ICOP), KUSZA Observatory and the Terengganu State Mufti Department provided a diverse set of images for this study. Two lightweight YOLO models (YOLOv11s and YOLOv8s) were trained using this dataset under similar conditions, with hyperparameter tuning conducted through random search. An evaluation on an independent test set showed that the YOLOv8s model, trained for 40 epochs with a batch of four, achieved excellent performance results by attaining a precision of 0.703 and a mean average precision of 0.735. These results indicate that the YOLOv8s model can identify the new crescent moon with greater accuracy and consistency compared to its predecessor. This provides a reliable and scalable alternative to traditional visual observation methods. The use of advanced object detection technology for calculating the lunar calendar is expected to enhance the accuracy and consistency of predicting the starting dates of Ramadan, Shawwal and Zulhijjah.*

***Keywords*:** New crescent moon; YOLO; Object detection; Lunar calendar

1. INTRODUCTION

Sighting of the new crescent moon plays a crucial role in determining the beginning of each lunar month in the Islamic calendar. Muslims worldwide participate in moonsighting every month to observe the new crescent moon and determine significant dates and events. This practice not only helps establish the calendar for religious observances but also strengthens community comradery among Muslims as they come together in anticipation and celebration of the lunar cycle. The moonsighting method varies, with some observe using the naked eye while others may rely on advancements in astronomical calculations and equipment to ensure accuracy in marking the start of each month.

Moonsighting, or the direct observation of the new crescent moon, remains a common practice, particularly in Muslim communities, even though *hisab* (calculation) offers a more precise method for determining the beginning of the lunar month [1]. The crescent moon's appearance marks each month's commencement in the Hijri calendar that translates the moon's synodic cycle into a familiar timekeeping framework. Observers on Earth calculate the initial sighting of the crescent using a set of parameters that trace back to Babylonian astronomy [2] and further refined by Muslim scholars, including Ibn Tariq, Al-Khwarizmi, Al-Tabari, Al-Battani, Al-Biruni, At-Tusi and others. According to Nasir et al. [3], these guidelines have evolved into regional standards, such as MABIMS (Malaysia, Brunei, Indonesia, and Singapore). However, these criteria merely serve as recommendations and do not guarantee the visibility of the new crescent moon. Factors such as inclement weather or a cloudy sky can obscure its sighting, and even when all prescribed conditions are met, the crescent may remain hidden. The general view is that there is a threshold beyond which the moon becomes unobservable, irrespective of weather conditions or the observer's visual acumen [4]. The *hisab* and *rukyah* methods converge based a set of criteria to interpret the new crescent moon according to Shari'a and astronomical principles. One example of a quantitatively interpretable criterion not explicitly mentioned in the al-Qur'an or Hadith is the determination of prayer times [5].

As a manifestation of science, technology has proven its ability to enhance convenience in everyday life [6]. Advancements in information technology have emerged as a key catalyst for change that significantly impacts various aspects of human existence, including health, education, transportation and other industries. Technology has become an integral component of human life in today's rapidly evolving technological landscape. Among the myriad categories of swiftly advancing information technology, only Big Data and artificial intelligence (AI) stand out for their remarkable progress. It is nearly inconceivable to envision human life without AI solutions today. Autonomous navigation has become a standard feature across all modern vehicles [7]. Dialogue surrounding the amalgamation of technology and religion has gained momentum among Muslims worldwide, particularly when considering recent technological advancements, including AI. These developments can potentially influence religious practices and how Muslims access knowledge about their faith [8, 9]. One example is the Internet of Things (IoT) technology that can act as an additional resource in the religious context. Applications, such as prayer reminders, digital Qurans and online religious courses, have made daily religious observance more accessible to Muslims. Technological innovations have also led to breakthroughs in areas such as image processing technology, which focuses on the computer manipulation of visual images for improving quality or extracting valuable information [10, 11]. One application of this technology is object detection, a computational technique for identifying visual items belonging to specific categories (such as animals or plants) in a digital image [12, 13, 14]. The goal is to develop computer models and methodologies capable of determining the detected object's type and location. Advancements in object detection technology has created new opportunities across various fields, including religious practices. The traditional limitations of observing the new crescent moon can be addressed by integrating object detection technology into these practices.

This study reviewed the literature on object detection related to identifying a new crescent moon. Studies [15] and [16] employed the Mask R-CNN system, which demonstrated high precision even under severe weather conditions. The YOLO technique is primarily used for object identification, as shown in several studies [17, 18, 19]. Studies [20] have endeavoured to develop a multi-object detection system for mobile devices that provides real-time nutritional information. The focus was on identifying food items in diverse and complex environments by utilizing a quantized YOLOv7 model to improve the efficiency of mobile apps for real-time object identification. This present study highlights the importance of model efficiency and size reduction for mobile applications with the quantized YOLOv7, though it is not designed explicitly for moon detection. One study [21] reported interesting findings using standard image processing techniques and the Circular Hough Transform for detecting young crescent moons from video footage. However, that study did not incorporate deep learning or YOLO, which could offer a more robust and automated approach. All the experiments demonstrated the feasibility of object detection. However, further refinement is necessary for developing a model that can swiftly and accurately detect a new crescent moon.

A literature review on image processing technology and the YOLO method in various object detection scenarios has identified several research gaps relevant to classifying new crescent moons using YOLO with video recordings. While the YOLO method has been widely applied for real-time object identification on mobile devices and in many different contexts, its application is meant for detecting astronomical events, such as the new crescent moon, although the Hijri calendar remains underexplored.

This present study had adopted a more integrated and comprehensive approach. It trained the model using images from ICOP, KUSZA Observatory and the Terengganu State Mufti Department’s database. This dataset was broader and more diverse, thus enhancing the reliability and validity of the study’s results. The YOLO algorithm was also employed in the developed model, as it has proven effective in detecting objects in images [22].

2. METHODOLOGY

This section will outline the approach for data collection and system development in this study.

2.1 Data Collection

The primary goal of this data collection method was to obtain high-quality data that can effectively address the research questions and thoroughly evaluate the hypotheses, while reducing bias to improve reliability and validity. The approach began with a comprehensive literature assessment carried out by the study utilizing various electronic resources, including digital monographs and peer-reviewed journal articles. After assembling the literature, the study rigorously analysed each source to extract the most relevant concepts, which then helped define the study's conceptual framework and direct its methodology’s design.

2.2 System Development

This study employed a prototyping methodology for system development. According to the Cambridge Dictionary, a prototype is an initial model of an object, such as a machine or industrial product, that serves as the basis for future versions [23]. Two key factors influenced the decision to use prototyping. Firstly, this approach is especially beneficial for applications that require continuous improvement, like machine-learning models, because it allows for rapid testing and hyperparameter optimization. This is essential for reducing overfitting and ensuring model accuracy. Secondly, prototyping enables the comparison of different algorithmic configurations. In this case, two iterations of the YOLO algorithm were evaluated for identifying the best option for categorizing crescent moons.

Prototyping enables quick iterations and assessments of models that offer valuable insight into the effectiveness of each option. This approach is particularly beneficial for projects without clearly defined requirements as it allows for early-stage research and flexibility. Preliminary testing and exploratory results can significantly influence future model development in these cases. The prototyping technique helps identify users’ needs, plan appropriate technological solutions, and ensure quality at every step of the development process. Fig. 1 illustrates the procedures involved in this prototyping technique.

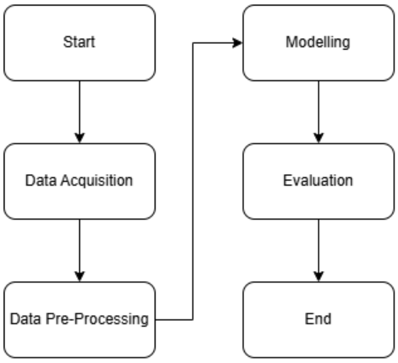

Fig. 1. Stages of the Prototyping Technique

Data Acquisition. This stage involved the collection of new crescent moon images from three sources, namely ICOP, KUSZA Observatory and Terengganu State Mufti Department. These institutions provided a diverse set of new crescent-moon images captured under varying aspects and environmental conditions. A total of 200 images were collected for use in this study and they all were consolidated into a single and systematically organized folder to streamline preprocessing. This single-class storage structure simplifies the dataset hierarchy and facilitates subsequent analysis that ensures efficiency and consistency in model development.

Data Preprocessing. The raw dataset underwent several technological modifications to make it suitable for analysis. These processes involved preparing the image files, labelling each crescent appearance, splitting the data into training, validation and test subsets, and implementing suitable augmentation techniques to enhance dataset diversity. This pre-processing improves data structure and readability, while optimizing accuracy and efficiency in subsequent analytical processes.

The primary objective of the data pre-processing step is to format the data, which involves organizing and standardizing the dataset into a consistent format. In this study, every image was converted to the PNG format to ensure uniformity and prevent file errors during training. The PILLOW library converted all non-PNG images into the required format. This stage ensures that each image meets the specified requirements for facilitating smooth processing throughout the model training phase. Fig. 2 shows the new crescent moon images before they were converted to PNG format.

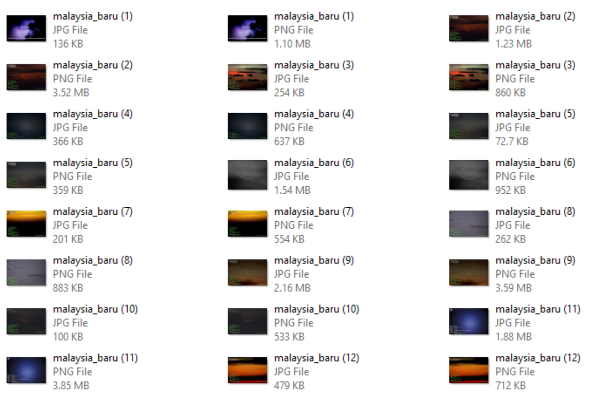

Fig. 2. Formatting results using PILLOW

The next phase involves data labelling or annotation. Each image is labelled with bounding boxes, one per image using a labelling software, corresponding to its designated category (see Fig. 3). This annotation step is essential for identifying the exact regions of interest that the machine-learning model will evaluate. Labelling improves the accuracy and overall performance of the model by guaranteeing that the input data are precisely annotated and aligned with analytical specifications.

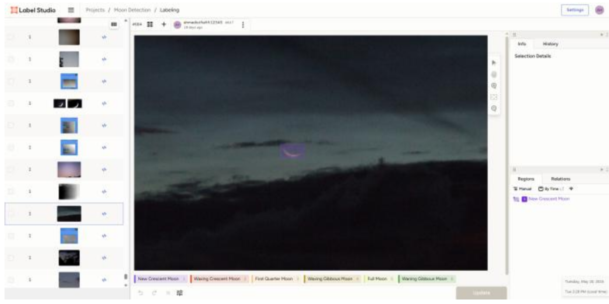

Fig. 3. Steps in the Data Annotation Process.

The annotated images were organized into three folders, namely training, validation and testing, along with their corresponding values (see Table 1). A careful sorting process was implemented to ensure that each subset displayed an even distribution of classes. This division method gives the model sufficient examples for optimizing parameters while maintaining independent datasets for validation and testing. This approach facilitates an unbiased evaluation of the model's performance and ability to generalize to new data.

Table 1. Dataset Partitioning Details

Dataset	Percentage (%)	Total
Training_data	96	192
Valid_data	2	4
Testing_data	2	4

In the last data pre-processing phase, augmentation is employed to introduce variability into the dataset and enhance the model's robustness to real-world conditions. Techniques, including grayscale conversion and image mirroring, were utilized (see Fig. 4) to produce inverted and tone-modified versions of the training images. These augmentation techniques increase the diversity of the training dataset and enhances the model's generalization to newer data and mitigate overfitting. This method resulted in an increase in the overall number of photos from 200 to 288, hence providing a greater number of scenarios for enhanced pattern recognition.

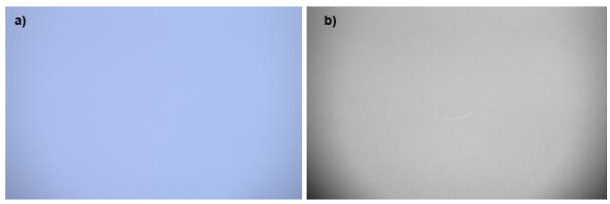

Fig. 4. Grayscale Augmentation: a) Raw image before augmentation, b) Grayscale image after augmentation

Modelling was conducted with two variations of YOLO namely YOLOv11 and YOLOv8. The adoption of YOLOv11 was motivated by its position as the latest version with architectural improvements, such as enhanced feature-fusion modules and optimized anchor-box mechanisms [24]. This provides a higher detection accuracy and stability relative to previous versions.

YOLOv11 was constructed based on the PyTorch framework [25], which offers dynamic computation graphs for efficient development and debugging while facilitating seamless deployment across numerous platforms. These characteristics make YOLOv11 exceptionally suitable for applications requiring exceptional accuracy and strong performance.

Meanwhile, YOLOv8 and YOLOv11 were chosen because of the innovative C2f backbone module, which mitigates concatenation bottlenecks and minimizes computational overhead [26]. The incorporation of the latest developments in network architecture allows YOLOv8 to deliver improved inference speed and detection performance while maintaining accuracy. The integration of YOLOv11's advanced feature-extraction skills with YOLOv8's efficient high-throughput design enables the creation of an object-detection system that is adaptable and effective in various operating contexts [27].

The starting point for training both YOLO versions on the selected dataset is to create a new crescent moon detection model. The main goal is to enhance precision detection and reduce visual limitations caused by adverse weather conditions. After completing the training, each model was subjected to evaluation and testing to assess its performance. Training begins with adjusting the hyperparameter's values that guide the learning process and eventually influence the model's output.

Hyperparameters for YOLOv11 and YOLOv8 were based on image size, number of epochs and batch size, with learning rate tuning included specifically for YOLOv8. Prudent selection of these parameters is essential for avoiding overfitting. Table 2 shows that epoch values of 40 are associated with a batch size of 6, all established through the Random Search method. This method involves an algorithm that meticulously investigates a predefined range or distribution of hyperparameter values that enable a structured search instead of manually adjusting them [28].

Table 2. Hyperparameter Configuration for YOLOv11 and YOLOv8 Models

Model	Epoch	Batch
YOLOv8	40	6
YOLOv11	40	6

The model-testing phase evaluates the system's ability to accurately recognize and localize objects using datasets that were not used in training, therefore providing appropriate generalization (see Fig. 5). This assessment is essential for evaluating the effectiveness of classification and localization in real-world scenarios. An additional error analysis shows the specific object classes or scenarios that frequently result in mispredictions, thus providing insight for focused improvements. These findings ensure that the model remains efficient and dependable across various situations.

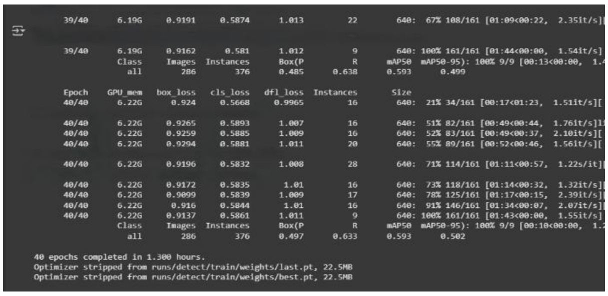

Fig. 5. Workflow of Model Training and Testing with Hyperparameter Configuration

The performance of YOLOv11 and YOLOv8 was evaluated on a separate test set, with findings summarized in Table 3. Evaluation metrics, such as accuracy, precision, recall and F1 score, were utilized to comprehensively assess each model's performance. Recall measures the capacity to identify all cases of the new crescent moon, precision assesses the frequency of false positives, and the F1 score combines these two metrics to guarantee effective detection without significant misclassification. Meanwhile, accuracy provides a general overview of correct predictions across all categories. This set of measures thoroughly assesses each model's strengths and limitations, thus, facilitating comparisons between YOLOv11's sophisticated feature-fusion processes and YOLOv8's efficient and high-throughput design in realistic operating conditions.

Table 3. Comparison of Precision, Recall, and F1-Score for YOLOv11 and YOLOv8

Model	Precision	Recall	F1-Score
YOLOv8	0.703	0.707	0.473
YOLOv11	0.758	0.733	0.553

3. RESULTS AND DISCUSSIONS

Training and evaluation were conducted on two configurations, namely YOLOv11 and YOLOv8. Each model was trained for 40 epochs with a batch size of six by using a Random Search-based hyperparameter tuning technique. Table 4 shows that both models attained a mAP@0.5 of 0.995. However, YOLOv8 exhibited a superior mAP@0.5–0.95 of 0.735 in contrast to YOLOv11's 0.683. This suggests that YOLOv8 exhibits superior accuracy under higher overlap criteria although both networks performed well at the usual 0.5 IoU threshold, indicating enhanced resilience in new crescent moon localization across various scenarios.

Table 4. Results of Random Hyperparameter Tuning for YOLOv11 and YOLOv8

Model	MaP 0.5	MaP 0.5-0.95
YOLOv8	0.995	0.735
YOLOv11	0.995	0.683

Three separate loss components were observed throughout training and validation, which are bounding box regression loss, object loss and classification loss, each calculated on a reserved sample extracted from the augmented dataset. YOLOv11 exhibited reduced aggregate loss rates during the training and validation stages compared to YOLOv8, thus underscoring its superior efficiency in the selected hyperparameter configuration.

Table 5. Training Loss Metrics for each model

Model	Box_loss	Cls_loss
YOLOv8	0.207	0
YOLOv11	0.985	0.59

Each model underwent direct testing with six new crescent-moon images following random hyperparameter tuning and loss assessment. This separate test set comprised four True Positive cases and two True Negative examples that enabled the evaluation of each model's detection accuracy and adaptability across different scenarios. The evaluation shows that YOLOv11 failed to detect the new crescent moon in several test samples, a shortcoming that corresponds with its comparatively high box and class losses (0.985 and 0.590), as reported in Table 5. In contrast, YOLOv8 achieved substantially better average accuracy, as reflected by its much lower loss values (box loss of 0.207 and class loss of 0.000), indicating more effective training and stronger generalization across varied scenarios.

The direct testing results (see Table 6) confirm that the YOLOv8 architecture is appropriately aligned with the selected hyperparameter setup. YOLOv8 attained an average accuracy of 73.2%, slightly outperforming YOLOv11's 71.5%. The stability and high accuracy highlights YOLOv8's dependability for classifying fresh crescent moons under diverse settings.

Table 6. Outcome of Direct Evaluation Based on Random Images

Model	Image					
	1	2	3	4	5	6
YOLOv8	76%	72%	83%	76%	70%	62%
YOLOv11	78%	65%	75%	72%	71%	68%

While the direct testing results showed favourable performance, it is crucial to acknowledge the various biases and limitations in the test set. The selected images may not represent the full range of real-life conditions, as differences in lighting, weather and environmental factors might not be sufficiently presented. This can lead to performance errors when the model encounters unfamiliar situations. In addition, resolution, noise levels and focus of the input images can significantly impact accuracy as poor-quality data can adversely affect model performance. These considerations highlight the importance of using diverse and high-quality test samples to ensure strong real-world applicability.

4. CONCLUSION

Based on the evaluations of this study it can be concluded that both YOLO versions were successful in new crescent moon classification, with YOLOv8 displaying better performance than YOLOv11. Despite the challenging visual circumstances, YOLOv8 was able to achieve faster and more accurate detections thanks to its simplified architecture and enhanced hyperparameter tuning. This was accomplished while still retaining high mAP scores and reduced loss values. YOLOv11 continues to be a reliable choice although it has shown to be more prone to greater loss rates and somewhat inferior generalization when compared to YOLOv8 and trained using the same batch and epoch configurations.

YOLOv8 demonstrated robust performance during the test by achieving a precision of 0.703 and a mean average precision (mAP@0.5–0.95) of 0.735. The training loss metrics (box loss of 0.207 and classification loss of 0.00) demonstrated excellent error reduction. In comparison, YOLOv11 displayed higher losses (box loss of 0.985 and class loss of 0.59), indicating a tendency for overfitting under the same hyperparameter configurations. Direct evaluation based on a random dataset of six new crescent moon images (four true positives and two true negatives) further verified YOLOv8's exceptional accuracy. These findings confirm YOLOv8 as the superior option for classifying new crescent moons.

Future attempts should involve supplementing the collection with images obtained directly from observatory telescopes at various global moonsighting locations in order to improve objectivity, including a broader range of weather circumstances. Furthermore, including live *in situ* testing of the classifier could supplement its practical utility. The preliminary study focused on YOLOv8s as a proof-of-concept; hence, future investigations should evaluate several lightweight variations under similar settings.

5. ACKNOWLEDGEMENT

The authors would like to extend their heartfelt gratitude to the Ministry of Higher Education (MOHE) Malaysia for funding this research under the Fundamental Research Grant Scheme (FRGS)-FRGS/1/2023/STG07/UNISZA/02/1. Special thanks to the Electromagnetic Research Group (EMRG) for their assistance in this study. Not forgetting ICOP, KUSZA Observatory and Terengganu Mufti State Department for providing the data for this study.

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