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Abstract:
The determination of the beginning of the Hijri month through the observation of the new moon is an important process that requires scientific support to account for decision-making. This study aims to develop a model for the classification of hilal visibility using Multinomial Logistic Regression (MLR) by utilizing observation data from the Meteorology, Climatology, and Geophysics Agency (BMKG) for the 2021–2025 period. Using data that includes astronomical and geometric parameters such as the Solar azimuth, the Moon's azimuth, the height of the Sun, the height of the Moon, the difference in azimuth, and the elongation. The label assigns the visibility of the new moon into three categories, namely Dark (elongation < 5°), Faint (5° ≤ elongation < 12°), and Light (elongation ≥ 12°). Obtain a total of 2210 lines of existing datasets, then divide the dataset into different training scenarios, namely 60/40, 70/30, and 80/20, with a standardization process before modeling. Optimized the model with the hyperparameter setting of the regularization constant C in the range of 0.001 to 100, using the saga solver and L2 penalty. The test results show that the model's performance improves as the C value increases. Obtained the best configuration at a 60/40 split with C = 100, resulting in an F1-Score of 99.10%, near-perfect accuracy and recall, and a ROC-AUC value close to 1. These findings show that MLR is effective in classifying elongation-based hilal visibility, as well as potentially being used as a basis for technical decision-making in determining the beginning of the Hijri month. However, this study still requires additional validation, such as stratified k-fold assays and cross-site or year testing, to ensure the model's generalization capabilities and avoid potential data leakage.

***Keywords*:** hilal visibility, elongation, classification, multinomial logistic regression

INTRODUCTION

The determination of the Hijri month for Muslim countries, including Indonesia, is an important part of Islamic religious practice, which relies heavily on the observation of the new moon cycle (Loucif et al., 2024). As a country with the largest Muslim population, Indonesia has a role and responsibility to ensure the accuracy of determining the beginning of the month, especially during the fasting months of Ramadan and Eid al-Fitr (Mohd Nawawi et al., 2024), (Rahmi et al., 2025). Traditionally, this determination is made through calculation (hisab) and observation (rukyat) for the appearance of a new hilal, which is also known as hilal (Koto et al., 2024; Ulum, 2021; Yunus, 2011). Although this practice is still ongoing, the integration of modern science and religious traditions is increasingly important to overcome challenges and ensure their accuracy (Sultan, 2007). However, these traditional methods often face challenges of accuracy and consistency due to poor weather conditions, unfavorable geographical locations, and very young lunar ages (Hussain, M., & Al-Mostafa, 2021), (Hoffman, 2003). This is also explained in the research of Taruna et al, who found that one of the important factors in determining the appearance of the new moon is the presence of high objects in locations that have the potential to obstruct the new moon (Taruna & Prakoso, 2017). Djamaluddin's research also explains that uncertainty in observation can cause differences in prayer times, thus creating uncertainty for Muslims (Djamaluddin, 2000). Improving accuracy as a way to avoid uncertainty continues to be pursued as much as possible. The Meteorology, Climatology, and Geophysics Agency (BMKG) has applied various technologies, one of which is the use of atomic clocks to measure Universal Time Coordinate (UTC) with high precision

in the observation of the new moon (Suprihatin et al., 2021), (BMKG, 2016). In addition, issues such as light pollution that interfere with observation are also other challenges that require adequate mapping and a deep understanding of atmospheric conditions (Badescu, 2008). Thus, the application of computational methods offers an innovative solution, which underlies the research of Muztaba et al, explaining that machine learning algorithms are able to improve the accuracy of new moon detection and create efficient automated programs (Muztaba et al., 2023). According to the results of Al-Rajab et al's research, a data-driven approach can significantly improve the accuracy of the prediction of moon visibility through advanced algorithms that use various machine learning methods, one of which is Logistic Regression (LR), which is a statistical-based machine learning algorithm but only uses models for binary classification problems (Al-Rajab et al., 2023). Other non-parametric models, such as Support Vector Machine (SVM) and Artificial Neural Network (ANN), have achieved high accuracy (>90%); these models are often considered black-boxes, making it difficult to identify the dominant factors affecting visibility (Al-Rajab et al., 2023). According to another study by Pinedo et al that analyzed the relationship between lunar phases and pregnancy incidence in Holstein cattle by applying artificial insemination using Multinomial Logistic Regression (MLR), although the results showed only a small association between the lunar cycle and pregnancy events, this study provides insight into biological factors in animals that may be affected by the lunar cycle (Pinedo et al., 2025). Multinomial Logistic Regression offers a clearer interpretation through the analysis of regression coefficients, making it suitable for providing policy recommendations for the Islamic calendar. Therefore, this study proposes an approach using Multinomial Logistic Regression to predict the visibility of the new moon based on the classification of the age of the moon, which is based on the legal basis of the Ministry of Religious Affairs on the criteria for the new moon (Khoeron, 2022; Odeh, 2004). With this research, it is hoped that it can provide innovative solutions and bridge the gap between tradition and scientific innovation in determining the Hijri/Lunar calendar.

This research offers the following contributions:

1. Identify the relationship and influence of astronomical factors, especially the age of the moon, on the visibility of the new moon.
2. Development and implementation of classification models that utilize multinomial logistic regression methods.
3. The results of this study support the decision to determine the hilal based on the age of the new moon for policymakers, especially the Ministry of Religion (Kemenag) and BMKG.

This article provides some important points. The Background section discusses the visibility criteria and the Multinomial Logistic Regression (MLR) method for the underlying classification of categories, and reviews the use of these methods in previous research approaches in Related Work. The Method and Data Preparation sections explain the MLR steps and data collection procedures. The Results and Discussions sections also discuss MLR experiments to classify the visibility categories of the new moon and validate the results. Finally, the Conclusion section discusses the results of the experiment and provides recommendations for further research.

RELATED WORK

Responding to several conceptual references related to the visibility of the hilal and the approach to using MLR and its application for pre-processing data, refer to Table 1. According to Mufid et al, the criteria for the hilal or hilal must be based on long-term astronomical observation data (Mufid & Djamaluddin, 2023). Furthermore, in the research, Hibaurrohman et al provide a more technical and mathematical perspective on the determination of the new hilal (Hibaurrohman et al., 2024). Meanwhile, according to Al-Rajab, the application of machine learning in predicting the visibility of the new moon based on criteria has proven effective (Al-Rajab et al., 2023). However, most of the research focuses more on the traditional aspects of hisab and rukyat, resulting in a lack of implementation of the current approach. This study relates the integration of Multinomial Logistic Regression (MLR) with new Hilal

classifiers based on categories in the context of the analysis of Hilal visibility in Indonesia is still minimal, especially in Malang Raya.

Table 1. Related Work for Hilal and MLR

Reference	Topic	Method	Subject
(Mufid & Djamaluddin, 2023), (Fuscha, 2021), (Rahmi et al., 2025)	Implementation of criteria for determining the day and the beginning of the month in the visibility of the new moon	Hisab	Unification of the Hijri calendar
			Know the distribution of the annual calendar pattern.
(Loucif et al., 2024), (Al-Rajab et al., 2023), (Gharaybeh, 2025), (Allawi, 2022)	Predictions and Criteria for the visibility of the new moon	Gradient Boosting, Extra Trees	Harmonization of the global lunar calendar
		Random Forest, SVM, KNN, Naive Bayes, Decision Tree	Predict the visibility of the new moon through a machine learning approach.
		Random Forest	Determination of the beginning of the month of Hijri
		ANN	Prediction of new Hilal visibility criteria
(Syuhada et al., 2023), (Syarif et al., 2025)	Mapping the position of the hilal to Mount Agung	Rukyat	Justification for assessing the visibility of the new hilal
(Koto et al., 2024), (Pramudya et al., 2024)	Light pollution monitoring and hilal monitoring	Hisab, Rukyat	Assess the capabilities of the tools and the feasibility of the observation location.
Our research	Categories of hilal visibility to elongation	Multinomial Logistic Regression	Elongation characteristics for hilal visibility

Previous studies have tended to focus on the traditional methods of hisab and rukyat that have long been used in determining the beginning of the month (Sultan, 2007). The application of Multinomial Logistic Regression is still fairly rare for use in the visibility of the new moon because this MLR is used for more than two categories, in contrast to the application of Logistic Regression, which only provides an output of two categories (Bowles, 2015). However, as the times evolve and the diversity of data, MLR has become one of the evolving classification techniques for modern data, making it possible to classify the visibility of the hilal not only as 'visible' or 'invisible', but also to consider complex and diverse additional factors that affect observation, geographic location, and observation time, each of which can become a new category or sub-category. According to research, Loucif et al recommended a machine learning (ML)-based framework to predict the visibility of the crescent moon, aiming to support decisions and mark the beginning of a new lunar month (Loucif et al., 2024). Then, in his research, Allawi explained that with the new criteria that divide into 4 regions: "invisible", "telescope only", "probably visible", and "definitely visible", depending on the width of the crescent moon and the arc of vision from the bright edge of the crescent moon (Allawi, 2022).

Given the limitations of previous research, which is still minimal in applying the integration of Multinomial Logistic Regression and classification in the analysis of the visibility of the new moon, especially in the Indonesian region, as well as the gap in observation of new moon data from BMKG that does not have a category label, this study is here to overcome these challenges. By offering a data-driven classification approach and machine learning algorithms, this study aims to complement the existing literature by presenting new perspectives and providing a more accurate and comprehensive understanding, so that it can be a reference for future researchers and governments.

MATERIAL AND METHOD

The two main components of methodology in this study are the method proposal and data preparation. The method recommendation section describes how to apply Multinomial Logistic Regression (MLR) to machine learning systems using categorical classification algorithms. This method utilizes hilal observation data collected throughout Indonesia by the Meteorology, Climatology, and Geophysics Agency (BMKG).

A. MATERIAL

The use in the preparation of data comes from the East Java Meteorology, Climatology, and Geophysics Agency (BMKG), especially from 34 hilal observation points in Indonesian territory. Twelve data variables are contained in this dataset, which includes the national dataset for the period 2021 to 2025. The presentation of variable information from each parameter is in Table 2.

Tabel 2. New Moon Observation Variables

Variable Name	Information
date	Data collection date
year	Hijri calendar year
location	Location of observation points
longtitude	Geographic longitude
latitude	Geographical latitude
sunset	Sunset time
moon sunset	Moonset time
sun azimuth	Sunset direction
moon azimuth	Direction of the moon setting
sun height	The height of the sun above the horizon
moon height	Height of the moon above the horizon
age	Age of the moon
elongasi	Moon elongation

However, this study used different elongation calculation data by adding the solar height variable to obtain a new elongation based on observation data. To obtain the height of the sun, researchers used a "reverse engineering" scenario based on astronomical calculations, by assuming the value of elongation (ψ) from direct observation data to get the Sun's height (h_S). Using the Cosine Ball Rule Formula (Odeh, 2004):

$$cos(\psi) = \big(\sin(h_M)\sin(h_S)\big) + \big(\big(\cos(h_M)\cos(h_S)\big).\cos(Az_M - Az_S)\big) \quad (1)$$

Notice that h_M appears in the form of $sin(h_M)$ dan $cos(h_M)$ thus forming trigonometric equations in the format $A\ cos(x) + B\ sin(x) = C$ which $C = cos(\psi)$ Become a reequation:

$$\big(cos(h_M)\ cos(Az_S - Az_M)\big).cos(h_S) + \big(sin(h_M)\big)\ sin(h_S) = cos(\psi) \quad (2)$$

Define if $A = cos(h_M)\ cos(Az_S - Az_M)$ dan $B = sin(h_M)$. To solve this equation, using the AAM (Auxiliary Angle Method) requires changing the shape. $A\ cos(h_M) + B\ sin(h_S)$ become $R\cos(h_S - \alpha)$, which $R = \sqrt{A^2} + B^2$. Earn grades α Using the formula $a = arctan\left(\frac{B}{A}\right)$. So that the equation becomes $R\cos(h_S - a) = C$ Forming the formula for the height of the sun into an equation:

$$h_S = a + arccos\left(\frac{cos(\psi)}{R}\right) \quad (3)$$

In field practice, this is rare because usually the height of the sun is data that is easier to obtain or calculate for a certain time than elongation. However, theoretically and mathematically, it is an excellent exercise for understanding the relationships between variables in a celestial triangle. Table 3 is the final dataset of the parameters contained in Table 2, and there are 2210 datasets in this study.

Tabel 3. New Elongation Data Based on Calculations

date	08-08-21	08-08-21	…	27-05-25	27-05-25
year	1443	1443	…	1446	1446
month	Muharram	Muharram	…	Zulhijah	Zulhijah
location	Banda Aceh	Medan	…	Manokwari	Jayapura
longtitude	95,1903	98,4124	…	134,0435	140,4195
latitude	5,3322	3,3451	…	-0,5176	-2,3268
sunset	18:54	18:03	…	18:03	17:33
moon sunset	18:54	18:37	…	18:10	17:39
sun azimuth	286	286	…	291	291
moon azimuth	290	290	…	296	296
sun height	0	0	…	4	0
moon height	0	0	…	1	0
age	6,5	6,5	…	7,7	7,0
elongasi	4	4	…	6	5

The main variables to classify the moon visibility category based on moon height and elongation, ignoring the age of the moon based on MABIMS criteria, are moon height 4° and elongation 6.4°. Underlying the elongation category, the classification focuses on three categories, as shown in Table 4.

Table 4. Hilal Category Label (MABIMS)

Category: Crescent	Elongation Range(°)
Dark	elongasi < 5
Vague	5 ≤ elongasi < 12
Light	elongasi > 12

B. METHOD

Multinomial Logistic Regression is an extension of Binary Logistic Regression when there are more than three or more categories that do not have a (nominal) sequence, in contrast to Logistic Regression, which only has two mutually exclusive categories. According to Pate et al., the multinomial logistic regression model allows predictions with results in more than two categories (Pate et al., 2023). According to El-Hapil, MLR is one of the important methods for categorical data analysis (El-Habil, 2012).

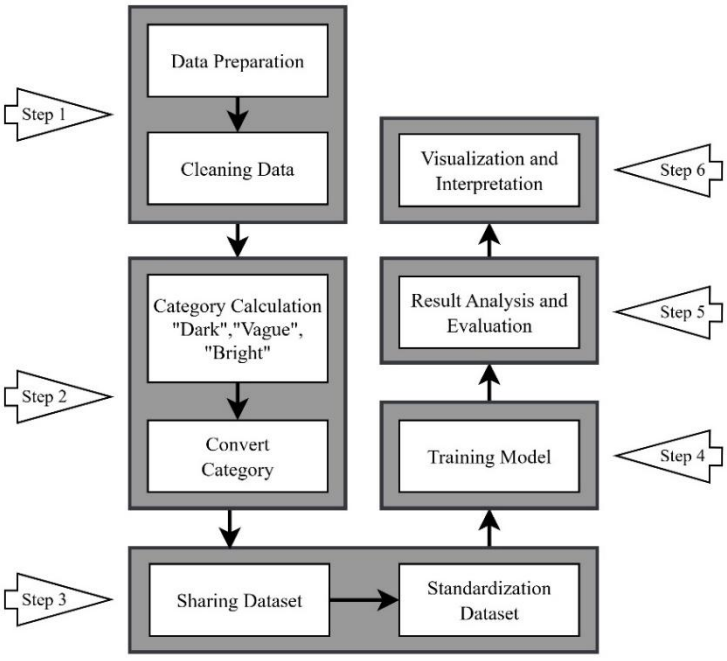


Figure 1. MLR flow system design of Hilal visibility category classification

Classifying categories on the visibility of the hilal can use Multinomial Logistic Regression. Initiate category classification with Multinomial Logistic Regression (MLR) in the following steps:

Step 1: Data Preparation

The data is on the official website page of the Meteorology, Climatology, and Geophysics Agency (BMKG), which is located at https://www.bmkg.go.id/tanda-waktu/hilal-gerhana. The dataset covers a period of 4 years from August 8, 2021, to May 27, 2025. Furthermore, carrying out the data cleaning process must be with consideration and caution; if there are inconsistent data, missing values, and errors in interpolation can cause fatal results in the model training process.

Step 2: Category Calculation

Before moving on to the next stage, categorization is one of the other main things after data cleansing. The calculation of the categories "Dark", "Vague", "Light" then converts to binary numbers 3, 2, and 1 using the equation:

$$f(elongasi) = \begin{Bmatrix} Dark & if\ elongasi < 5 \\ Vague & if\ 5 \leq elongasi < 12 \\ Light & jika\ elongasi > 12 \end{Bmatrix} = \begin{Bmatrix} 3 \\ 2 \\ 1 \end{Bmatrix} \quad (4)$$

Step 3: Sharing the Dataset and the Standardization Dataset

Once the dataset usage is ready, it further divides the dataset into 60:40, 70:30, 80:20, and 90:10. Then, after the dataset is divided into several models, the dataset goes through a standardization process using StandardScaler, which is a preprocessing method to erase the mean and scale in the form of variant units (Menard, 2011).

$$X_{standard} = \frac{X^{-mean(x)}}{standard\ deviation(x)} \quad (5)$$

$$x = \sum_{i=1}^{n} \frac{x_i}{n} \quad (6)$$

Step 4: Training Model

After completing the previous steps, the next step is to train models 1 to 4 using MLR in combination with parameter tuning. Supporting this, according to Pedregosa et al, the scikit-learn documentation recommends hyperparameter tuning by testing different combinations of parameters to find the best one (Pedregosa et al., 2011), (Bowles, 2015).

$$ln = \left[\frac{P(Y=k)}{P(Y=1)}\right] = \beta_{0,k} + \sum_{q=1}^{Q} \beta_{q,k} X_q \quad (7)$$

$$\sum_{k=1}^{K} P(Y=k) = 1 \quad (8)$$

The Optimization process uses solver parameters to determine the use of algorithms as well as the optimal model coefficient (weight) and penalty setting to select the type of regularization norm (for example, L1 or L2), while C functions to control the inversely proportional regularization force. A smaller C value will result in stronger regularization.

Step 5: Result Analysis and Evaluation

The results of various tunings will stop when the accuracy value displays a number of 1.00, which indicates that the performance has been excellent. In this study, the determination of parameter adjustment focuses on finding differences based on each model by utilizing the simplification of the classification pattern that presents data reports in the form of a matrix coefficient format based on accuracy, precision, recall, and an overview of AUC (Area Under Curve) to measure model performance (Allawi, 2022).

Step 6: Visualization and Interpretation

The last stage is the stage for the MLR process classification. The interpretation of the model on the visual (matrix coefficient) produces insights that underlie the determination of various parameter tunings. The validation process has a role to ensure the conformity of the results with the requirements, to obtain the model with the smallest error value (Loucif et al., 2024).

RESULT

A. DATA PREPARATION

The research variables used the variables of month height, azimuth, and elongation shown in Table 2. Presenting data on the visibility of the hilal, which is the basis for the next analysis process, is found in Table 3, with a total dataset of 2210.

B. CATEGORY CALCULATION

Perform the category calculation process using Python code based on the calculations found in equation 4, which aims to provide categorical values as outputs.

C. DATASET SHARING AND DATA STANDARDIZATION

Dividing the dataset into three main models is contained in Table 5, each consisting of six variants (A1-A6, B1-B6, C1-C6). By differentiating each parameter based on a combination of training parameters, it aims to make it easier to perform performance comparisons to determine the model with the most optimal prediction results.

Table 5. Model Dataset Sharing

Model	Dataset	
	Training	Testing
A	60	40
B	70	30
C	80	20

After the dataset division, standardizing the data aims to equalize the weight of each feature. Table 6 gives the results of the values that have passed the standardization process in the form of a variance unit scale.

Table 6. Dataset Standardization

year	-1.366	-1.366	…	-1.366	-1.366
longtitude	-0.622	-0.299	…	-1.274	2.624
latitude	-1.057	-1.027	…	0.601	0.123
sun_azimuth	-0.270	-0.270	…	1.470	1.350
moon_azimuth	-0.296	-0.044	…	1.368	1.368
different_azimuth	0.363	-0.965	…	-0.699	-1.231
hight_sun	1.582	-1.084	…	-0.600	0.612
hight_moon	1.570	-0.950	…	-0.492	0.654
elongasi	1.343	-0.719	…	-0.837	0.636

D. TRAINING MODELS

The process of training the model provides insight to see and get information from each tuning parameter and find the optimal combination of values for the hyperparameters of a machine model to improve its performance. This process is important to avoid overfitting or underfitting, as well as ensuring that the model is able to learn accurately and efficiently.

Modelling Data

To ensure that the model can work optimally, hyperparameter tuning performs a process on a variety of scenarios. Table 7 shows the details of the configured being tested, including the varying data sharing as well as the adjustment of the C value for each model. The goal is to find the best combination of parameters that produces the most accurate performance.

Table 7. Tunning Parameter Model

Model	Data	C Value	Solver	Penalty
A	60/40	0.001	saga	l2
	60/40	0.01	saga	l2

	60/40	0.1	saga	l2
	60/40	1	saga	l2
	60/40	10	saga	l2
	60/40	100	saga	l2
B	70/30	0.001	saga	l2
	70/30	0.01	saga	l2
	70/30	0.1	saga	l2
C	80/20	0.001	saga	l2
	80/20	0.01	saga	l2
	80/20	0.1	saga	l2

Model A

Table 8. Tuning Parameter Model A

Model	Training Data	C	Solver	Penalty
A1	1326	0.001	saga	l2
A2	1326	0.01	saga	l2
A3	1326	0.1	saga	l2
A4	1326	1	saga	l2
A5	1326	10	saga	l2
A6	1326	100	saga	l2

Perform performance testing of model A in Table 8 by conducting a series of experiments that vary the value of hyperparameter C. Establishing the data division at a 60/40 ratio, 1326 data points are used for training. Each row (A1 to A6) represents a model A test with a different C value, ranging from 0.001 to 100, while the solver and penalty stick to 'saga' and 'l2'.

Model B

Table 9. Tunning Parameter B

Model	Training Data	C	Solver	Penalty
B1	1547	0.001	saga	l2
B2	1547	0.01	saga	l2
B3	1547	0.1	saga	l2
B4	1547	1	saga	l2
B5	1547	10	saga	l2
B6	1547	100	saga	l2

The next experiment in Table 9 focuses on Model B, applying a 70/30 data sharing ratio. Allocating 1547 data as training data to train models. This table shows how the engine tests this model with a variation in the value of C from 0.001 to 100, while still maintaining other parameters with constants, such as solvers and penalties.

Model C

Table 10. Tunning Parameter C

Model	Training Data	C	Solver	Penalty
C1	1768	0.001	saga	l2
C2	1768	0.01	saga	l2
C3	1768	0.1	saga	l2
C4	1768	1	saga	l2
C5	1768	10	saga	l2
C6	1768	100	saga	l2

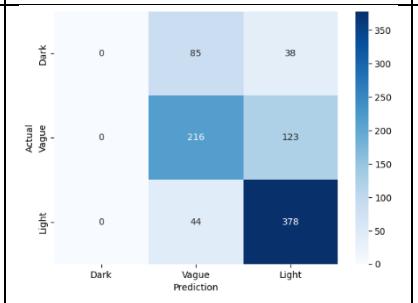
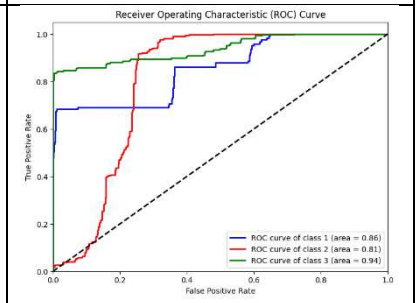
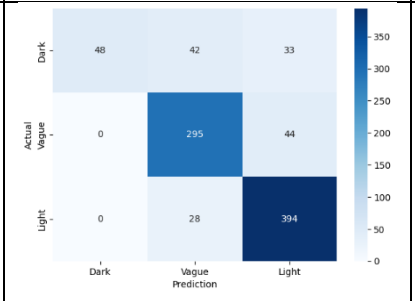
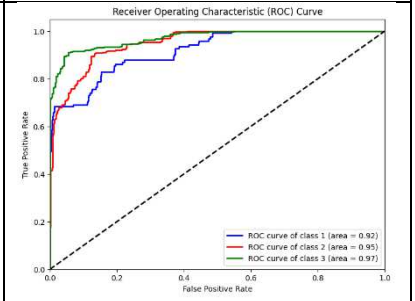
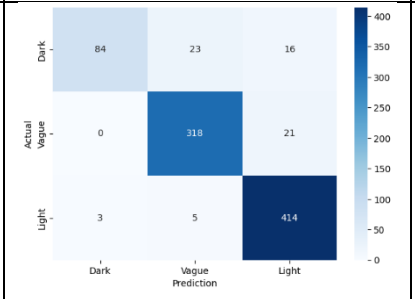
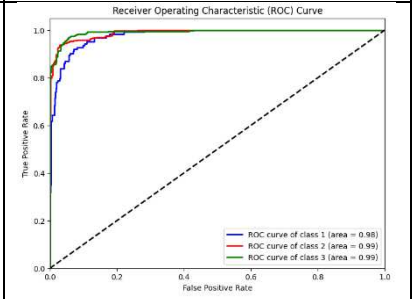
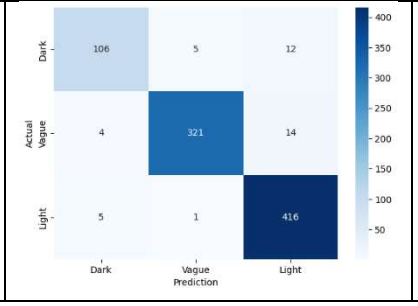
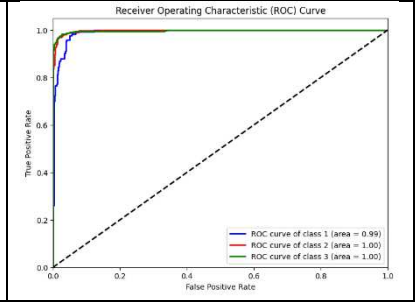
Table 10 details the experimental configuration for Model C the training data ratio is increased to 80% of the total dataset, which is 1768 datasets. Perform a series of tests by varying the values of the

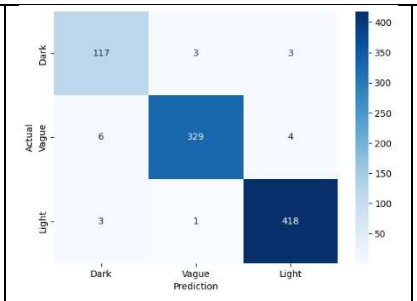
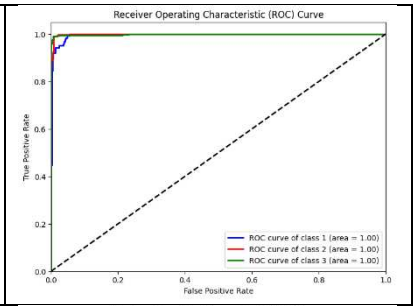
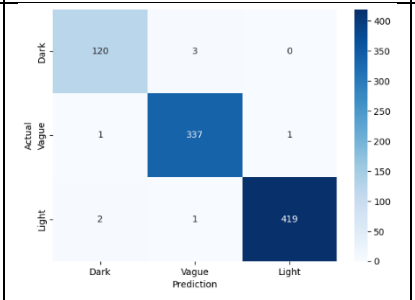
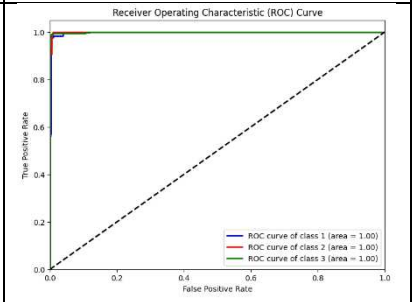
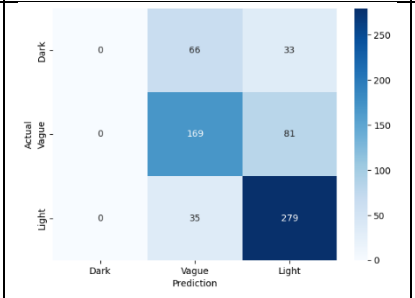
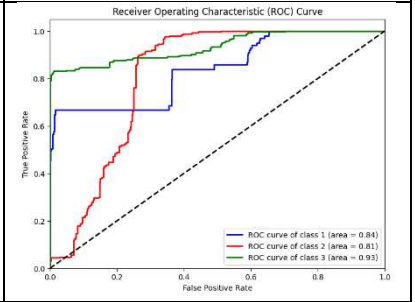
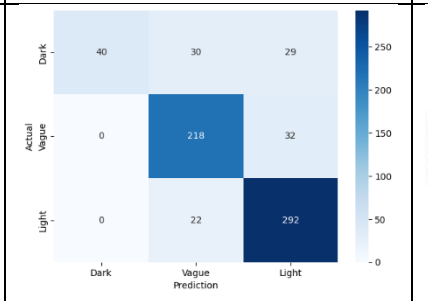
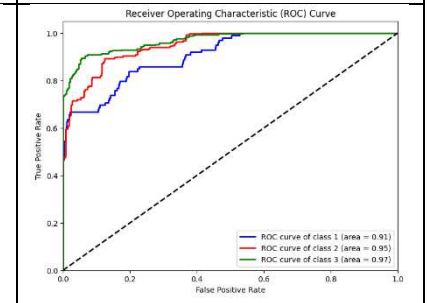
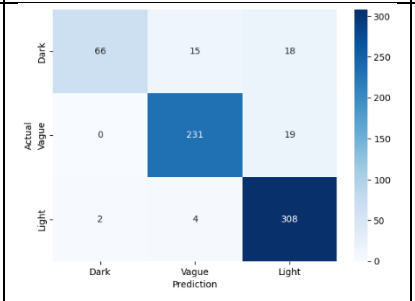
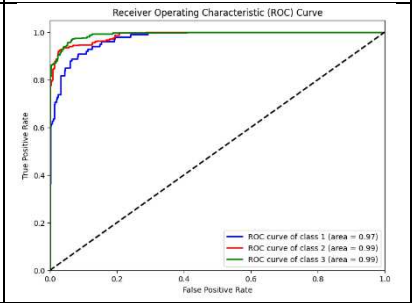
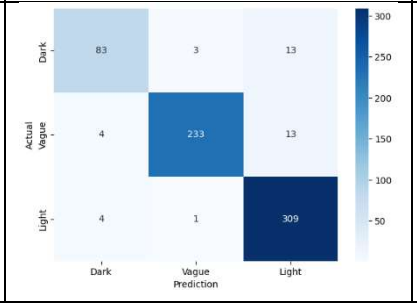
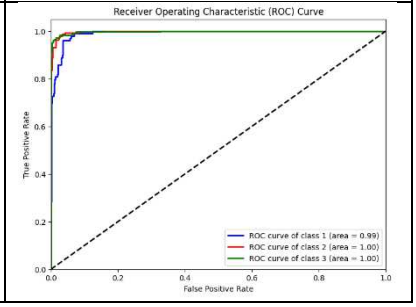
hyperparameter C (0.001, 0.01, 0.1, 1, 10, 10, 100) to identify the optimal combination. Maintains other configurations, such as 'saga' solver and penalty 'l2'.

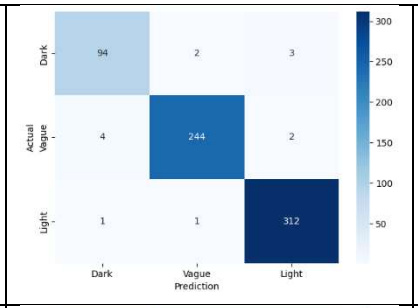
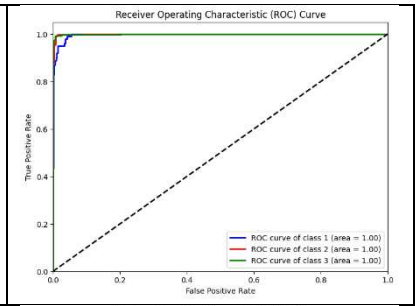
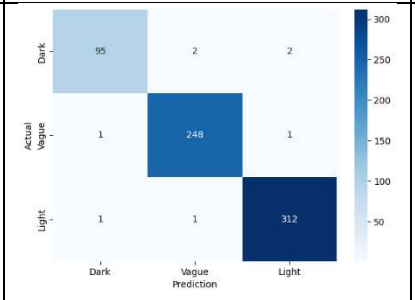
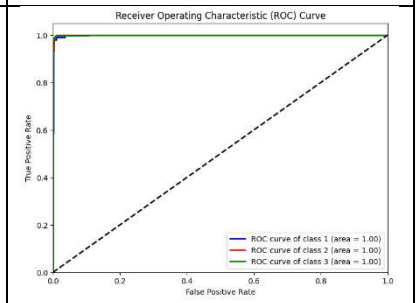
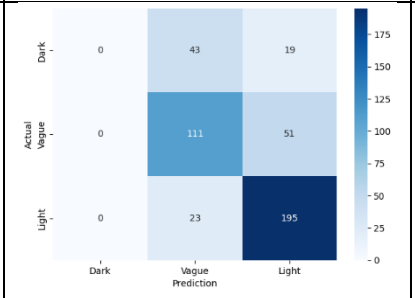
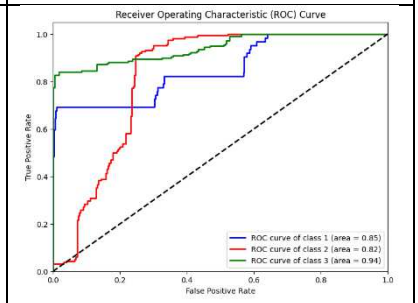
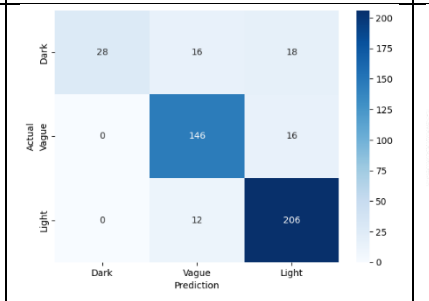
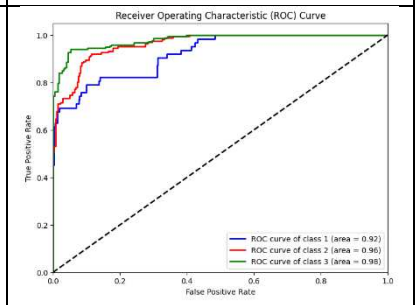
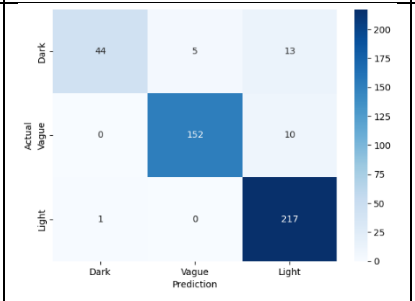
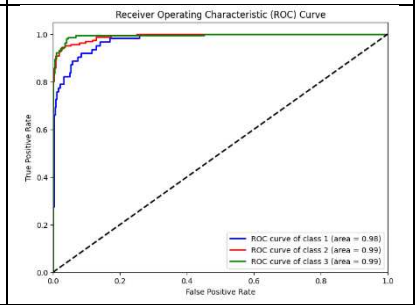
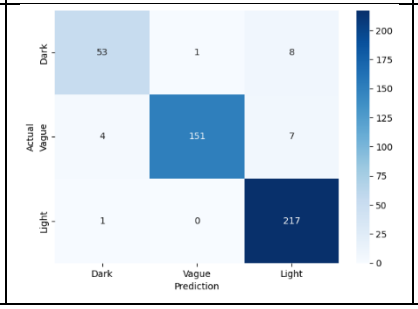
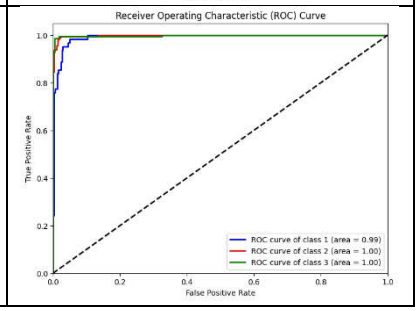
Results of Model Tuning Parameters

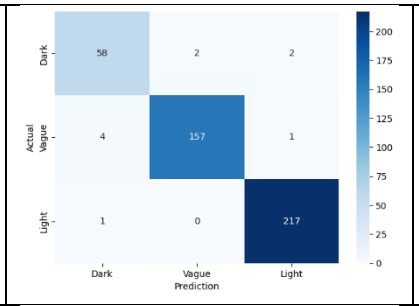
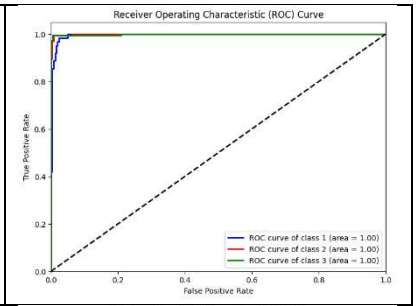
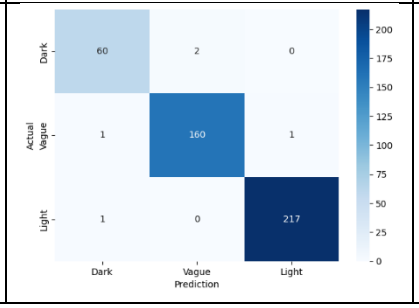
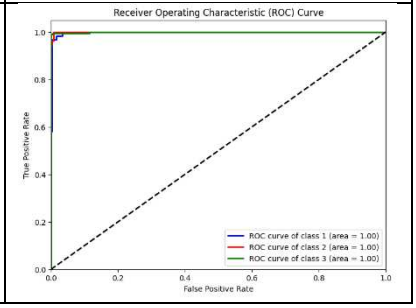
The development of model performance is very evident through the Confusion Matrix belonging to each series (A, B, and C). Early models such as A1, B1, and C1 show a significant degree of misclassification, characterized by a considerable spread of values off the main diagonal. This phenomenon indicates the difficulty of the early models to accurately distinguish between the 'Dark', 'Vague', and 'Light' categories. As the evaluation moves towards the next models, there is a concentration of values along the main diagonal. The peak performance, achieved by the A6, B6, and C6 models, presents a matrix with a near-perfect picture. The results showed the consistency of almost all predictions with the actual value, which was visually characterized by the darkest-colored diagonal cells contrasting with other very low or zero cells.

Table 11. Graphic Model

Model	Metric	ROC-AUC
A1		
A2		
A3		
A4		

A5		
A6		
B1		
B2		
B3		
B4		

B5		
B6		
C1		
C2		
C3		
C4		

C5		
C6		

This positive trend was also strongly confirmed through the analysis of the ROC-AUC curve. The ROC curve of the early models looks more sloping and does not stick tightly to the upper left corner, an indication of moderate discriminating ability. As the model's performance improves, the curves move progressively closer to the ideal shape, which is a right angle in the upper left corner. The best models, such as the C6, feature an excellent performance ROC curve with an Area Under the Curve (AUC) value of 1.00. This achievement signifies the model's near-perfect ability to differentiate between one class and another. Thus, this visual evidence conclusively supports the conclusion of the analysis that the tuning process has succeeded in significantly improving the accuracy and predictability of the model and producing a highly reliable final model for the study of lunar visibility.

Table 12. Parameter Tuning Model Results

Model	Solver	Penalty	C	F1-Score	Precision (m.avg/w.avg)	Recall (m.avg/w.avg)
A	saga	l2	0.001	67.19%	0.44/0.57	0.51/0.67
			0.01	83.37%	0.88/0.84	0.73/0.83
			0.1	92.31%	0.93/0.93	0.87/0.92
			1	95.36%	0.95/0.95	0.93/0.95
			10	97.74%	0.97/0.98	0.97/0.98
			100	99.10%	0.99/0.99	0.99/0.99
B	saga	l2	0.001	67.57%	0.45/0.57	0.52/0.68
			0.01	82.96%	0.88/0.85	0.74/0.83
			0.1	91.25%	0.93/0.92	0.86/0.91
			1	94.27%	0.94/0.94	0.92/0.94
			10	98.04%	0.97/0.98	0.97/0.98
			100	98.79%	0.99/0.99	0.98/0.99
C	saga	l2	0.001	69.23%	0.45/0.59	0.53/0.69
			0.01	85.97%	0.90/0.87	0.77/0.86
			0.1	93.44%	0.95/0.94	0.88/0.93
			1	95.25%	0.95/0.95	0.93/0.95
			10	97.74%	0.96/0.98	0.97/0.98
			100	98.87%	0.98/0.99	0.98/0.99

Based on the results of the parameter tuning process presented in Table 12, an in-depth analytical conclusion is drawn. This process aims to determine the optimal hyperparameter C value for the multinomial logistic regression model in predicting the hilal visibility category. The data shows the identification of a consistent and significant trend in all three models (A, B, and C). Measurement of

model performance through F1-Score, Precision, and Recall shows an increase that is in line with the increase in the value of the C parameter. In contrast, when raising the C value, the model's performance increases drastically, reaching its peak at the value of C = 100.

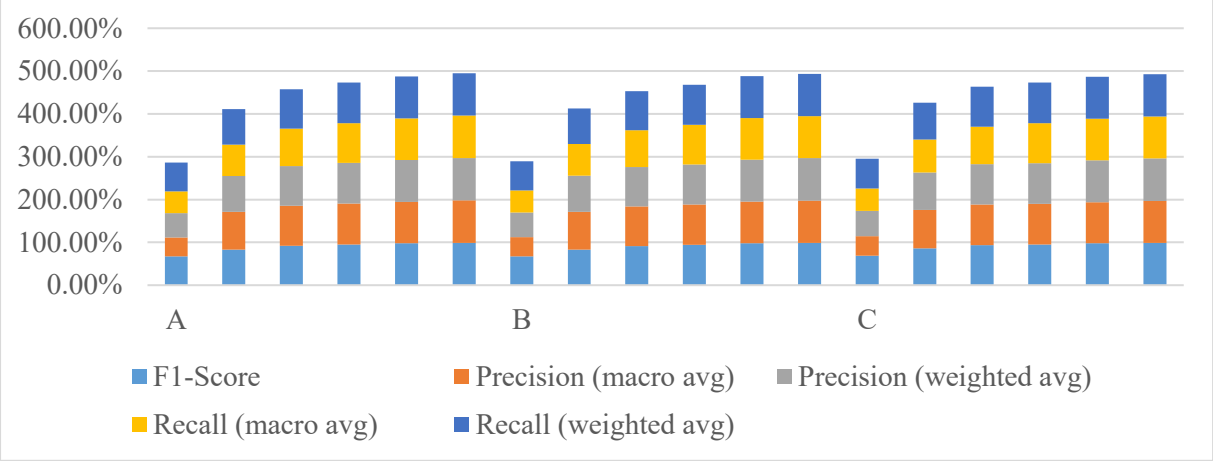


Figure 2. Chart Analysis

In Figure 2, the graph shows that Parameter B provides the most stable and consistent metric scores compared to Parameters A and C. Although the Recall and Precision scores (both macro avg and weighted avg) in Parameters A and C are sometimes higher, the variation is much greater. This indicates that Parameter B has more reliable performance.

Specifically, the Model A with a C value of 100 appears as the most superior configuration, with an F1-Score of 99.10%, as well as near-perfect Precision and Recall values (0.99). The high level of these metrics indicates that the model not only has a very high precision in making predictions, but also a comprehensive ability to identify the entire actual case in each visibility category. The equivalence between the macro average and weighted average values further confirms that the model has balanced and reliable capabilities in all three classes ('Dark', 'Vague', and 'Light').

While these results are very satisfactory, achieving near-perfect scores requires vigilance against potential overfitting. Therefore, it is highly recommended to further validate this optimal model using completely independent test data. This step is crucial to ensure that the superior performance that the model demonstrates can pass through the generalization well to the new data.

DISSCUSION

Existing tests prove that the integration of Multinomial Logistic Regression (MLR) in classification is an effective approach to analyze the pattern of moon visibility to elongation, with the main variables used being moon height and elongation. The results of the analysis show that there are three classifications with three different labels, so that MLR is suitable to be used to classify the category of elongation of the visibility of the new moon in Indonesian territory. In Loucif et al's research, various Machine Learning algorithms such as Gradient Boosting, Random Forest, Logistic Regression, and SVM were used with the support of feature optimization techniques and ensemble learning, which resulted in predictions of global hilal visibility (Loucif et al., 2024). The main variables used include astronomical and geographical parameters, such as elongation (ARCL), lunar age, Sun-Moon lag time, altitude and azimuth of the Moon and Sun, illumination, atmospheric conditions, and latitude and longitude coordinates. However, this study applies a different approach because it focuses on the classification of elongation using MLR. Meanwhile, Al-Rajab et al's research applied the Random Forest algorithm and Support Vector Machine to predict the visibility of the new moon, especially at the beginning of the month of Ramadan, with fairly accurate prediction results, even though the dataset used is still limited (Al-Rajab et al., 2023). The variables analyzed included lunar age, lag time, lunar altitude, azimuth difference (DAZ), elongation (ARCL), arc of vision (ARCV), illumination, and atmospheric

conditions. Meanwhile, this study emphasizes the use of MLR to produce three classifications with three elongation labels, which are effective for determining the visibility of the new moon in Indonesian territory.

CONCLUSION

This study succeeded in building a moon visibility classification model using Multinomial Logistic Regression (MLR) based on BMKG observation data for the 2021–2025 period. The model utilizes astronomical and geometric parameters such as the Moon's azimuth, the Sun's azimuth, the Moon's height, the Sun's height, the difference in azimuth, and the elongation, with labeling into three categories: Dark, Faint, and Light. The results of the experiments showed that the performance of the model improved with constant adjustment of the regularization C the best configuration at a 60/40 split data with C = 100 resulted in an F1-Score of 99.10%, near-perfect precision and recall values, and a ROC-AUC close to 1.0. This proves that MLR can effectively map the relationships between parameters to classify hilal visibility with very high accuracy.

These findings imply that MLR not only offers a competitive level of accuracy compared to other methods, such as Random Forest or Support Vector Machine, but also provides interpretability through model coefficients that can be used to explain the influence of each parameter on the visibility of the hilal. Thus, MLR has a strong potential to support technical decision-making in determining the beginning of the Hijri month in a more transparent and scientific data-based manner.

For further research, it recommends the use of stratified k-fold validation to ensure more robust model performance, as well as testing on external data from different observation locations and periods. In addition, the adjustment of the visibility category of the new moon needs to be aligned with international standards such as the MABIMS criteria or the Global Islamic Calendar (KIG) criteria, or if different, it needs to provide a strong scientific justification. The presentation of the model coefficients, along with the analysis of the direction and magnitude of the influence of each parameter, is also important to strengthen the interpretation. With these improvements, the MLR model is expected to be widely operationalized as a decision support system in the determination of the Hijri calendar, as well as contribute to increasing accuracy and transparency in the field of modern astronomy.

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ETHICS DECLARATION

The authors declare that no ethical approval was required for this study, as it did not involve human participants, human data, or animals.

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