An Intelligent Machine-Learning System for Automated Inheritance-Share Prediction Based on Maliki Jurisprudence

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Abstract

This study aims to develop an intelligent computer program that applies machine-learning techniques to inheritance problems in accordance with Maliki jurisprudence and automatically predicts the shares of heirs. The jurisprudential framework of the proposed system is based on major Maliki references, including al-Mudawwana al-Kubrā of Sahnūn, al-Risālah of Ibn Abī Zayd al-Qayrawānī, al-Maʿūnah ʿalā Madhhab ʿĀlim al-Madīnah of Qāḍī ʿAbd al-Wahhāb al-Baghdādī, Mukhtaṣar Khalīl of Khalīl ibn Isḥāq al-Jundī, Mawāhib al-Jalīl li-Sharḥ Mukhtaṣar Khalīl by al-Ḥaṭṭāb al-Ruʿaynī, al-Sharḥ al-Kabīr of al-Dardīr, and Ḥāshiyat al-Dusūqī. These references were used to establish the rules governing the fixed shares of heirs, residuary inheritance, exclusion and impediment, ʿawl, radd, the two al-Gharāwayn cases, al-Akdarīyah, and cases involving the grandfather and siblings.

Two independent datasets differing in size and case-construction methodology were used. The first dataset consisted of 2,000 cases generated computationally by a reference engine for calculating inheritance shares. It was divided into 1,600 training cases and 400 independent test cases. The second dataset comprised 500 documented and structured inheritance cases derived from recognized Maliki jurisprudence sources, including 400 training cases and 100 independent test cases.

Three machine-learning models were evaluated: Random Forest, XGBoost, and a Multilayer Perceptron neural network. Model performance was assessed using four main metrics: mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and the coefficient of determination (R^2).

On the independent test set of the first dataset, XGBoost achieved the best performance, with an MAE of 0.000161, an RMSE of 0.000497, a MAPE of 0.32%, and an R^2 value of 0.999950. Random Forest also performed well, obtaining an MAE of 0.000435, an RMSE of 0.001624, a MAPE of 0.98%, and an R^2 value of 0.999166. In contrast, the MLP neural network recorded an MAE of 0.003368, an RMSE of 0.005761, a MAPE of 4.76%, and an R2 value of 0.383832.

For the second dataset, consisting of 500 cases and an independent test set of 100 cases, XGBoost again outperformed the other models, achieving an MAE of 0.000199, an RMSE of 0.000597, a MAPE of 0.18%, and an R^2 value of 0.999978. Random Forest obtained an MAE of 0.001440, an RMSE of 0.007175, a MAPE of 5.18%, and an R^2 value of 0.996685, whereas the MLP model achieved an MAE of 0.004218, an RMSE of 0.009064, a MAPE of 3.44%, and an R^2 value of 0.715004.

The significance of this study lies in integrating the science of Islamic inheritance, Maliki jurisprudence, databases, and artificial intelligence into a unified computer-based system capable of receiving the composition of heirs and automatically generating their corresponding shares. Each case can also be linked to its relevant jurisprudential reference, thereby enhancing transparency, introduction verification, and scientific review. Nevertheless, high statistical performance—particularly on cases generated by the reference computational engine—does not, by itself, constitute evidence of jurisprudential validity. Final validation requires comparison with documented cases, consultation of the aforementioned Maliki references, and expert review of exceptional cases, including ʿawl, radd, al-Gharāwayn, al-Akdarīyah, cases involving the grandfather and siblings, and inheritance impediments.

Keywords: Maliki jurisprudence; Islamic inheritance; inheritance shares; machine learning; XGBoost; artificial intelligence

1-Introduction

The science of Islamic inheritance, known as ʿilm al-farāʾiḍ, is one of the most systematic and mathematically precise branches of Islamic jurisprudence. It concerns the identification of eligible heirs, the determination of their prescribed shares, the rules of exclusion and impediment, and the distribution of the deceased's estate in accordance with Islamic law. Its principal foundations are found in the Qur'anic verses of Sūrat al-Nisāʾ **[1]**, particularly verses 11, 12, and 176, which establish the main fixed shares of heirs, including one-half, one-quarter, one-eighth, two-thirds, one-third, and one-sixth. These rules were further explained through the Prophetic tradition and applied by the Companions, especially Zayd ibn Thābit, ʿAlī ibn Abī Ṭālib, ʿAbd Allāh ibn ʿAbbās, and ʿAbd Allāh ibn Masʿūd, who contributed significantly to the development of inheritance jurisprudence **[2].**

During the early Islamic period, inheritance questions were resolved through the interpretation of revealed texts, Prophetic traditions, genealogical analysis, and arithmetic reasoning. Zayd ibn Thābit was particularly recognized for his knowledge of inheritance and was consulted in difficult succession cases **[3].** Muslim jurists gradually transformed these principles into a structured legal and mathematical discipline. They developed methods for distinguishing between fixed-share heirs and residuary heirs, identifying excluded heirs, determining inheritance impediments, and resolving cases in which the prescribed shares exceeded or fell short of the estate. Among the most important procedures are ʿawl, which involves the proportional reduction of shares when their total exceeds the estate, and radd, which involves returning the remaining estate to eligible heirs when no residuary heir is present **[4]**. Other complex cases include the two al-Gharāwayn cases, al-Akdarīyah, the inheritance of the grandfather with siblings, and several forms of partial and complete exclusion **[5]**.

Before the development of modern computing, inheritance calculations were performed manually by jurists, judges, notaries, and specialists in Islamic law. The main tools used in this process included genealogical diagrams, tables of heirs, fractional operations, common denominators, proportional calculations, and the determination of the aṣl al-masʾalah, or original denominator of the inheritance problem **[6]**. The traditional method generally began by identifying all potential heirs, excluding those prevented from inheriting, assigning the fixed shares, distributing the residue to residuary heirs, and applying exceptional rules such as ʿawl and radd. Although this method was mathematically rigorous, complex cases involving several heirs, multiple relationships, or exceptional legal rules could require considerable time and specialized expertise **[7]**.

The Maliki school has preserved and developed a substantial body of literature on inheritance and family law. One of its earliest major references is al-Muwaṭṭa by Imām Mālik ibn Anas, who died in 179 AH / 795 CE [8]. Although the work is primarily a collection of hadith and legal traditions, it contains important foundations related to family law and inheritance. Another fundamental source is al-Mudawwana al-Kubrā, compiled by Sahnūn ibn Saʿīd al-Tanūkhī, who died in 240 AH / 854 CE, based mainly on the legal opinions transmitted by Ibn al-Qāsim from Imām Mālik **[9]**. This work is considered one of the principal references of Maliki jurisprudence and includes detailed discussions of inheritance shares, residuary heirs, exclusion, and exceptional cases.

An important concise reference is al-Risālah by Abū Muḥammad ʿAbd Allāh ibn Abī Zayd al-Qayrawānī, who died in 386 AH / 996 CE **[10]**. This work became one of the most influential introductory texts in the Maliki school and presents a summarized account of the principal inheritance rules. Al-Maʿūnah ʿalā Madhhab ʿĀlim al-Madīnah was written by Qāḍī ʿAbd al-Wahhāb al-Baghdādī al-Mālikī, who died in 422 AH / 1031 CE**[11]**. It is a comprehensive legal manual that explains the positions of the Maliki school and contains discussions relevant to inheritance and family law.

Among the most influential later Maliki works is al-Bayān wa al-Taḥṣīl by Ibn Rushd al-Jadd, who died in 520 AH / 1126 CE **[12]**. This work examines legal questions through transmitted opinions and provides extensive analytical discussions. Mukhtaṣar Khalīl, written by Khalīl ibn Isḥāq al-Jundī, who died around 767 AH / 1365 CE, became one of the central legal summaries of the Maliki school **[13]**. Its condensed formulation led to the production of several important commentaries, including al-Tāj wa al-Iklīl li-Mukhtaṣar Khalīl by al-Mawwāq, who died in 897 AH / 1492 CE **[14]**, and Mawāhib al-Jalīl li-Sharḥ Mukhtaṣar Khalīl by al-Ḥaṭṭāb al-Ruʿaynī, who died in 954 AH / 1547 CE **[15]**. Later references include al-Sharḥ al-Kabīr by al-Dardīr, who died in 1201 AH / 1786 CE, and Ḥāshiyat al-Dusūqī by Muḥammad ibn Aḥmad al-Dusūqī, who died in 1230 AH / 1815 CE**[16]**. These works are particularly important for clarifying the relied-upon Maliki positions and explaining complex inheritance questions.

The development of arithmetic, databases, and computer programming subsequently created new possibilities for automating inheritance calculations. Early computer programs were generally based on rule-based expert systems that represented jurisprudence principles through conditional statements, decision trees, tables, and mathematical formulas. Such systems could identify eligible heirs, assign fixed shares, apply exclusion rules, determine the original denominator, and calculate the final distribution. They offered important advantages by reducing repetitive arithmetic, improving consistency, and decreasing the time required to solve inheritance cases. However, rule-based systems remained dependent on the completeness and accuracy of the programmed legal

rules and were often unable to deal flexibly with unforeseen combinations of heirs or complex jurisprudence cases.

The emergence of artificial intelligence and machine learning introduced new approaches to the computational treatment of Islamic inheritance. Artificial intelligence can assist in organizing jurisprudential knowledge, processing case descriptions, retrieving relevant references, identifying heirs, and supporting legal and educational applications. Machine learning enables computational models to learn patterns from previously solved cases and apply them to new cases. Recent research has begun to examine artificial intelligence, large language models, and automated systems for Islamic inheritance reasoning and distribution. Some recent studies have evaluated large language models on Islamic inheritance cases and reported promising results for models with advanced reasoning capabilities, while also emphasizing the difficulty of applying fixed shares, exclusion rules, ʿawl, and radd consistently **[17]**. Other studies have explored the use of generative artificial intelligence for Islamic legal and inheritance applications, but they have also highlighted the necessity of expert supervision and jurisprudential verification **[18]**.

Despite these developments, research combining machine learning with the Maliki school's inheritance methodology remains limited. Existing studies have often focused on direct arithmetic calculators, rule-based applications, chatbots, or the general evaluation of language models. Fewer studies have compared several supervised machine-learning models using independent datasets that combine computationally generated cases with documented cases extracted from recognized jurisprudential sources. Furthermore, many existing tools do not associate each inheritance case with a specific jurisprudential reference, which limits transparency, traceability, and scholarly review**.[19]**

The application of artificial intelligence and machine learning to Islamic inheritance has scientific, social, economic, legal, and religious significance. Scientifically, it creates an interdisciplinary field linking Islamic jurisprudence, mathematical modeling, computer science, database construction, and artificial intelligence. It allows researchers to construct structured datasets, compare algorithms, assess predictive accuracy, and develop explainable computational methods. Socially, an intelligent inheritance program may help families understand the distribution of estates and reduce disputes caused by misunderstanding or arithmetic errors. Economically, automation may reduce the time, effort, and cost required to analyze a large number of inheritance cases. Legally, such a system could assist notaries, legal researchers, courts, estate administrators, and institutions responsible for applying inheritance regulations by organizing information and documenting the calculation process**.[20]**

From a religious perspective, however, artificial intelligence must be regarded as an assisting tool rather than an independent authority for issuing fatwas or establishing the validity of a legal judgment. The statistical accuracy of a model does not, by itself, prove the jurisprudential correctness of its results. The validity of an automated inheritance system depends on the correctness of its legal rules, the reliability of its data, the interpretation of the applicable Maliki position, and the accurate treatment of exceptional cases. For this reason, any computational result should remain subject to comparison with authoritative references and review by qualified jurists and legal specialists. This precaution is particularly important because evaluations of generative

AI have reported inconsistencies in complex inheritance matters, including exclusion, *al-radd*, *al-ʿaw*, *al-Akdarīyah*, homicide, religious difference, and the inheritance of residuary heirs.**[21]**

The present study addresses this research gap by developing an intelligent computer program for predicting inheritance shares according to Maliki jurisprudence. The system is based on major Maliki references, including al-Muwaṭṭaʾ, al-Mudawwana al-Kubrā, al-Risālah, al-Maʿūnah ʿalā Madhhab ʿĀlim al-Madīnah, al-Bayān wa al-Taḥṣīl, Mukhtaṣar Khalīl, al-Tāj wa al-Iklīl, Mawāhib al-Jalīl, al-Sharḥ al-Kabīr, and Ḥāshiyat al-Dusūqī. It uses two independent datasets constructed according to complementary approaches. The first dataset contains 2,000 computationally generated cases produced by a reference inheritance engine, while the second contains 500 documented and structured cases derived from recognized Maliki jurisprudential sources.**[22]**

Three machine-learning models—Random Forest, XGBoost, and a Multilayer Perceptron neural network—are trained and evaluated using the mean absolute error, root mean square error, mean absolute percentage error, and coefficient of determination. The purpose is to determine the most accurate model, evaluate its performance on independent cases, and assess the possibility of integrating jurisprudential references with machine-learning methods for inheritance prediction. The proposed system is intended to calculate and distribute the shares of heirs in ordinary, exceptional, and complex cases, including cases requiring special treatment under Maliki jurisprudence.**[23]**

The interest of this research lies in the development of an extensible tool that can support scientific research, the teaching of Islamic inheritance, and the study and application of Maliki jurisprudence in Algeria and other countries. The program may help reduce the time, effort, and costs required to resolve inheritance problems while maintaining transparency and reference-based verification. It can also be improved through the integration of larger and more diverse datasets, additional documented cases, new machine-learning algorithms, explainable artificial intelligence, and continuous review by jurisprudential experts. Accordingly, the proposed system is not designed to replace jurists, judges, or religious authorities; rather, it is intended to assist them by providing rapid, structured, reproducible, and scientifically assessable computational support.**[24]**

The proposed program is designed as an extensible framework that can be further improved through the integration of larger and more diverse datasets, additional documented cases, and advanced machine-learning models. It may serve as a valuable tool for scientific research and for supporting the study and application of Maliki jurisprudence in Algeria and other countries where this school of jurisprudence is followed. In its current form, the system is intended to calculate and distribute the shares of heirs, including ordinary, exceptional, and complex inheritance cases. By assisting researchers and specialists in the analysis and resolution of inheritance problems, the program may contribute to reducing the time, effort, and costs required for their examination, while preserving the need for jurisprudential verification and expert review.**[25]**

2-Computational Method

The computational methodology was designed to evaluate the ability of machine-learning models to predict inheritance shares according to the Maliki jurisprudential framework. Two independent Excel datasets were used. The first dataset contained 2,000 cases generated by a reference inheritance-calculation engine, whereas the second dataset contained 500 documented and

structured cases extracted from recognized Maliki jurisprudential sources. In both datasets, the target values corresponded to the inheritance shares generated by the reference calculation engine. Therefore, the obtained results measure the ability of the machine-learning models to reproduce the computational target values and should not be interpreted independently as proof of jurisprudential validity.

The first dataset contained 2,000 cases and was divided into 1,600 cases for training and 400 cases for independent testing. The second dataset contained 500 cases, including 400 training cases and 100 independent test cases. The independent test sets were not used during model training and were reserved for evaluating the generalization performance of the models on previously unseen cases.

Three supervised machine-learning models were evaluated: Random Forest, XGBoost, and a Multilayer Perceptron (MLP) neural network. Random Forest is an ensemble method that combines multiple decision trees and aggregates their predictions. XGBoost is a gradient-boosting algorithm that builds an additive sequence of decision trees, with each successive tree attempting to reduce the errors made by the previous trees. Its regularization mechanisms and boosting strategy make it suitable for modeling complex nonlinear relationships. The MLP neural network consists of interconnected layers of artificial neurons and is capable of learning nonlinear relationships between the input characteristics of inheritance cases and the corresponding heir shares.

The dataset-processing procedure included loading the Excel files, identifying the input variables and target values, checking the structure of the data, and separating the features from the target variables. The datasets were then divided into training and independent testing subsets according to the predefined proportions. For the neural-network model, the input variables were normalized to improve the stability and convergence of the optimization process. The tree-based models were trained using the same input structure, while the MLP model was trained using the normalized features. The prediction results of all three models were subsequently compared with the reference target values.

Four regression metrics were used to evaluate model performance: mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and the coefficient of determination (R^2). MAE measures the average absolute difference between the predicted and reference values. RMSE gives greater weight to larger errors because the residuals are squared before averaging. MAPE expresses the average absolute error as a percentage of the reference value, whereas R^2 measures the proportion of the variance in the target values explained by the model.

The computational experiments were performed using the two Excel files shown below:

- قاعدة_بيانات_المواريث_المالكية_خليل_2000_حالة.xlsx, containing 2,000 cases.
- 500_حالة_مواريث_مالكية_من_الكتب.xlsx, containing 500 cases.

For the first dataset, the independent test set contained 400 cases. For the second dataset, the independent test set contained 100 cases.

The strong performance of XGBoost indicates that the model was highly effective in reproducing the numerical patterns generated by the reference inheritance engine. Additional validation against independently reviewed cases, specialist evaluation, and direct comparison with authoritative

Maliki references remain necessary, particularly for complex cases involving ʿ*awl*, *radd*, al-Gharāwayn, al-Akdarīyah, the grandfather with siblings, and inheritance impediments.

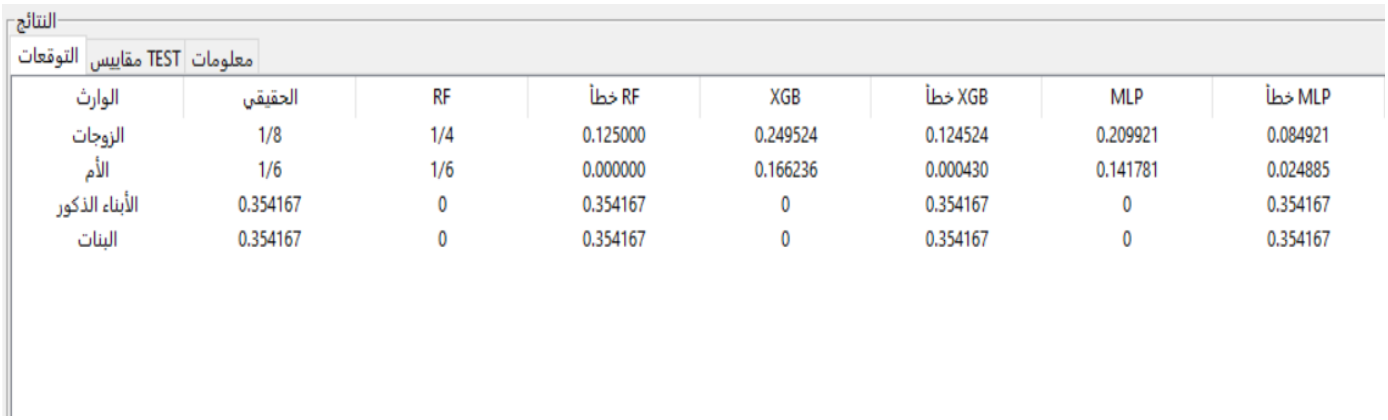
The computational framework is extensible and can be improved by increasing the size and diversity of the datasets, adding more documented Maliki cases, incorporating expert-validated labels, testing additional algorithms, and applying explainable machine-learning techniques. Such improvements may strengthen the system's usefulness for scientific research, the teaching of Islamic inheritance, and the development of digital tools supporting the application of Maliki jurisprudence in Algeria and other countries.

3-Results and Discussion

3-1. Datasets and Reference Framework

Two independent datasets were used to evaluate the machine-learning models.

The first dataset, خليل_المالكية_المواريث_بيانات_قاعدة_2000_حالة.xlsx, contained 2,000 inheritance cases. It was divided into 1,600 training cases and 400 independent test cases.**Fig.1** The second dataset, الكتب_من_مالكية_مواريث_حالة_500.xlsx, contained 500 documented and structured cases, including 400 training cases and 100 independent test cases.


النتائج

التوقعات | مقاييس TEST | معلومات

الوارث	الحقيقي	RF	خطأ RF	XGB	خطأ XGB	MLP	خطأ MLP
الزوجات	1/8	1/4	0.125000	0.249524	0.124524	0.209921	0.084921
الأم	1/6	1/6	0.000000	0.166236	0.000430	0.141781	0.024885
الأبناء الذكور	0.354167	0	0.354167	0	0.354167	0	0.354167
البنات	0.354167	0	0.354167	0	0.354167	0	0.354167

Figure 1. Prediction of the first dataset: 2,000 inheritance cases.

The second dataset was constructed from cases related to Maliki jurisprudence and was organized using major Maliki references **Fig.2**, including *al-Muwaṭṭaʾ* by Mālik ibn Anas, *al-Mudawwana al-Kubrā* by Sahnūn, *al-Risālah* by Ibn Abī Zayd al-Qayrawānī, *al-Maʿūnah ʿalā Madhhab ʿĀlim al-Madīnah* by Qāḍī ʿAbd al-Wahhāb, *al-Bayān wa al-Taḥṣīl* by Ibn Rushd al-Jadd, *Mukhtaṣar Khalīl*, *al-Tāj wa al-Iklīl*, *Mawāhib al-Jalīl*, *al-Sharḥ al-Kabīr*, and *Ḥāshiyat al-Dusūqī*. These references provide the jurisprudential basis for the fixed shares, residuary inheritance, exclusion, impediment, *ʿawl*, *radd*, al-Gharāwayn, al-Akdarīyah, and cases involving the grandfather and siblings.

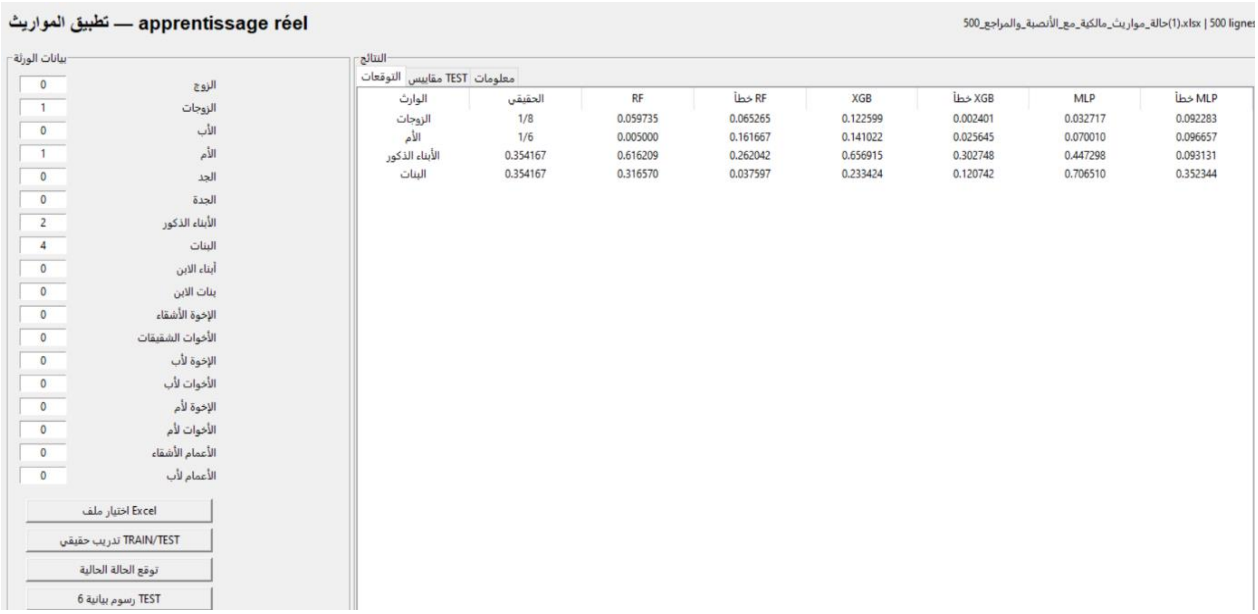


Figure 2. Prediction of the first dataset: 500 inheritance cases.

It is important to clarify that the target values in both datasets were generated by the reference computational engine. Therefore, the machine-learning models were evaluated according to their ability to reproduce the numerical outputs of this engine. High predictive performance should consequently be interpreted as strong computational agreement with the reference engine and not, by itself, as independent proof of the jurisprudential validity of every result.

3-2. Machine-Learning Models

Three supervised machine-learning models were compared: Random Forest, XGBoost, and a Multilayer Perceptron neural network. Random Forest is an ensemble algorithm that constructs multiple decision trees and combines their predictions. Its principal advantages include robustness, the ability to model nonlinear relationships, and relatively low sensitivity to individual observations. However, its performance may decrease when the target function contains highly precise or complex numerical relationships. XGBoost is a gradient-boosting model that constructs decision trees sequentially. Each new tree is trained to reduce the residual errors produced by the previous trees. Through boosting and regularization, XGBoost can capture complex nonlinear relationships while controlling overfitting. This algorithm is particularly suitable for structured tabular data and regression tasks. The MLP neural network is composed of interconnected layers of artificial neurons. It can learn nonlinear relationships between input variables and inheritance shares. Nevertheless, its performance depends strongly on data size, feature scaling, network architecture, hyperparameter selection, and the availability of sufficiently diverse training examples.

3-3. Evaluation Metrics

The models were evaluated using four regression metrics: mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and the coefficient of determination (R2).MAE measures the average absolute difference between the predicted and reference inheritance shares. RMSE gives greater importance to large prediction errors because the residuals are squared before averaging. MAPE expresses the prediction error as a percentage, while R2 indicates the proportion of the variance in the reference targets explained by the model.

3-4. Results for the 2,000-Case Dataset

The first dataset contained 2,000 cases, with 1,600 cases used for training and 400 cases reserved for independent testing. The target values were generated by the reference computational engine.Fig.3-a

Table 1. Performance of the models on the 2,000-case dataset

Model	MAE	RMSE	MAPE	R^2
Random Forest	0.000439	0.001630	0.99%	0.999158
XGBoost	**0.000168**	**0.000477**	**0.33%**	**0.999950**
MLP Neural Network	0.003368	0.005761	4.76%	0.383832

XGBoost achieved the best results for all four-evaluation metrics. It obtained an MAE of 0.000168 and an RMSE of 0.000477, indicating that its predictions were very close to the reference values. Its MAPE was only 0.33%, while the R^2 value of 0.999950 indicates that the model explained almost all of the variance in the target values.

Random Forest also produced a high R^2 value of 0.999158 and a low MAPE of 0.99%. However, it was less accurate than XGBoost, particularly in terms of MAE and RMSE. The MLP model showed considerably weaker performance, with an MAE of 0.003368, an RMSE of 0.005761, a MAPE of 4.76%, and an R^2 of only 0.383832. This result suggests that the MLP model did not adequately learn the numerical relationship between the input characteristics and the target inheritance shares in this experiment.

Compared with Random Forest, XGBoost reduced the MAE by approximately 61.7% and the RMSE by approximately 70.7%. Compared with the MLP model, it reduced the MAE by approximately 95.0% and the RMSE by approximately 91.7%.

3-5. Results for the 500-Case Dataset

The second dataset consisted of 500 documented and structured cases based on Maliki jurisprudential sources. It was divided into 400 training cases and 100 independent test cases. **Fig.3-b**

Table 2. Performance of the models on the 500-case dataset

Model	**MAE**	**RMSE**	**MAPE**	**R^2**
Random Forest	0.002378	0.014201	4.38%	0.990019
XGBoost	**0.000297**	**0.001017**	**0.15%**	**0.999962**
MLP Neural Network	0.016901	0.042880	12.04%	0.597430

XGBoost again achieved the best performance on the independent test set. It obtained an MAE of 0.000297, an RMSE of 0.001017, and a MAPE of 0.15%. Its R^2 value of 0.999962 demonstrates an exceptionally strong agreement between its predictions and the reference target values.

Random Forest maintained a high R^2 value of 0.990019, but its errors were substantially higher than those of XGBoost.

The MLP model showed the weakest performance, with an MAE of 0.016901, an RMSE of 0.042880, a MAPE of 12.04%, and an R^2 value of 0.597430.Compared with Random Forest, XGBoost reduced the MAE by approximately 87.5% and the RMSE by approximately 92.8%. Compared with the MLP model, it reduced the MAE by approximately 98.2% and the RMSE by approximately 97.6%.

(a) **(b)** the 2000-case

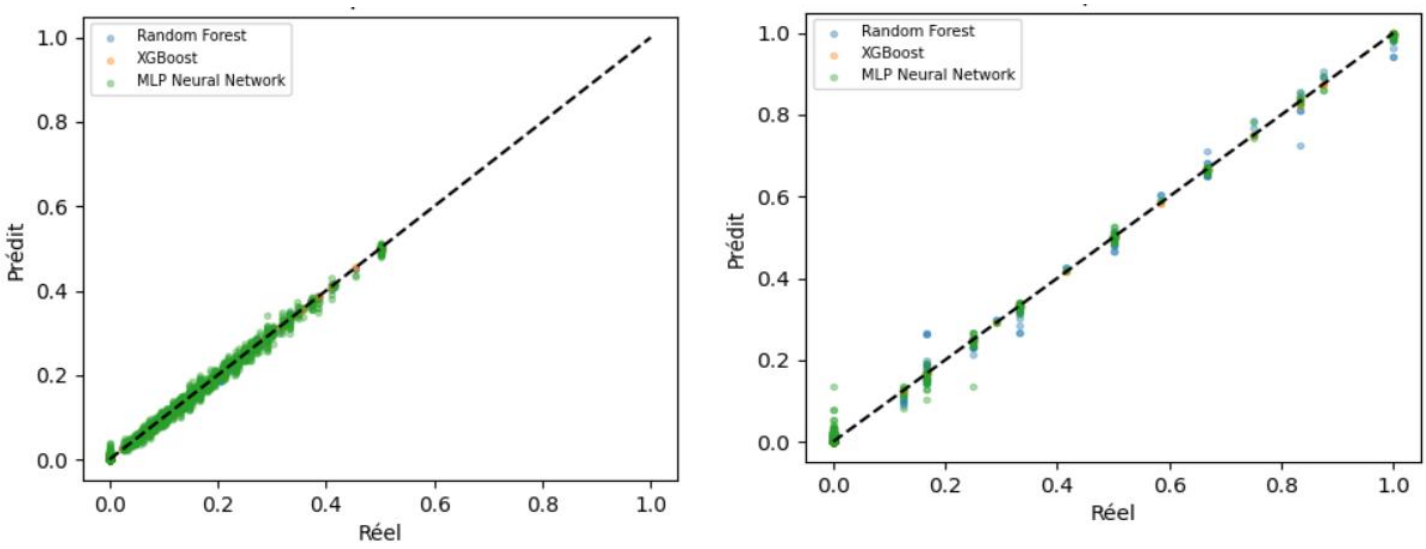


Figure 3 Actual vs predicted – test

for the 2000-case for the 500-case

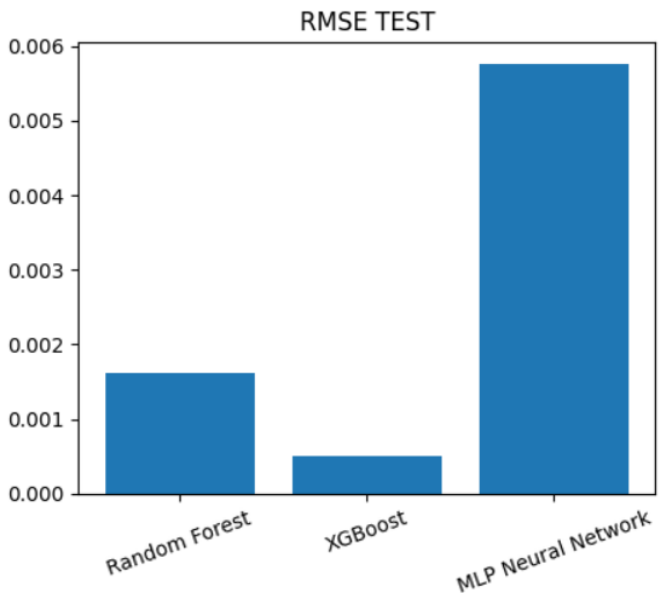
3-6. Comparative Analysis

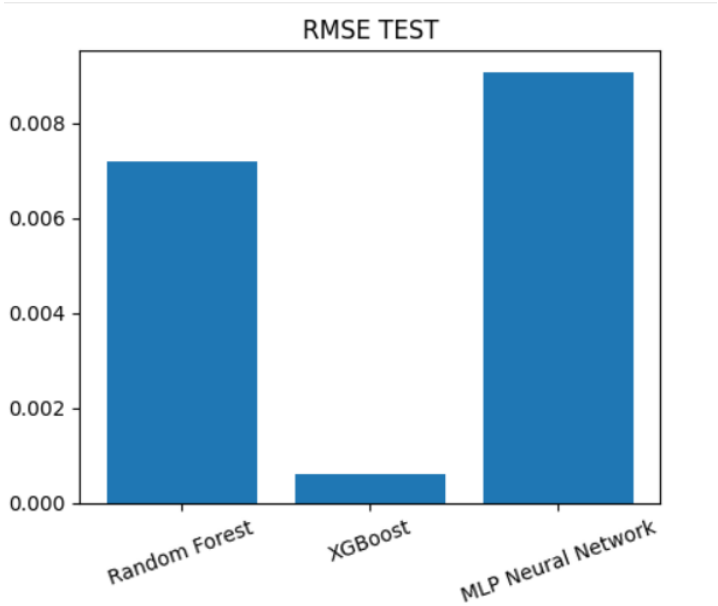
Table 3. Comparative performance of XGBoost across both datasets

Dataset	MAE	RMSE	MAPE	R2
2,000 cases	0.000168	0.000477	0.33%	0.999950
500 cases	0.000297	0.001017	0.15%	0.999962

XGBoost was the best-performing model in both experiments. Its R^2 values were higher than 0.9999 on both independent test sets, and its MAPE remained below 0.35%. These results indicate that XGBoost was highly effective in reproducing the target values generated by the reference engine.

The error values were somewhat higher for the 500-case dataset in terms of MAE and RMSE **Fig.4,** although its MAPE was lower than that obtained for the 2,000-case dataset. This difference may be related to the structure and diversity of the cases, the distribution of the target shares, and the presence of more complex jurisprudential combinations in the documented dataset. The high R^2 value nevertheless indicates that the model preserved a strong correspondence with the reference outputs.





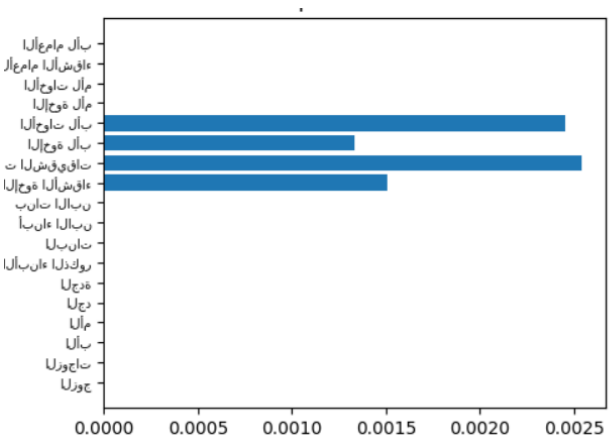
The error values for the 2000-case The error values for the 500-case

Figure .4 The error values

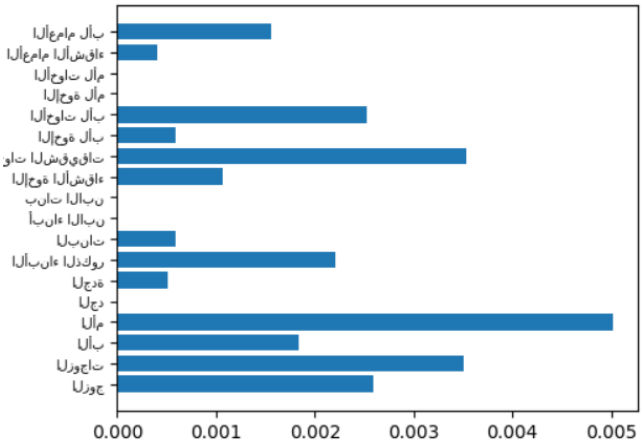
3-7. Prediction and Error Analysis

To evaluate the behavior of the models in greater detail, the predicted values should be compared with the reference values for every independent test case. Figure X illustrates the Mean Absolute Error (MAE) obtained by the Random Forest model for each heir category. The results demonstrate that the prediction error varies across the different categories of heirs. Lower MAE values indicate a closer agreement between the predicted inheritance shares and the reference shares, while higher values indicate relatively greater prediction errors. Overall, the relatively small MAE values observed across the heir categories indicate that the Random Forest model provides accurate predictions for most inheritance-share variables, although certain categories remain more challenging to predict.

Figure 5 Variation in the prediction error across the different categories of heirs



MAE for the 2000-case



MAE for the 500-case

A notable difference can be observed between the two datasets when analyzing the MAE by heir category. In the 500-case source-based dataset, non-zero prediction errors are observed across a broader range of heir categories. This behavior is consistent with the greater diversity of documented inheritance configurations derived from Maliki jurisprudential references. In contrast, the 2,000-case computationally generated dataset shows noticeable MAE values mainly for four heir categories,**Fig.5** while the remaining categories exhibit zero or negligible errors. This difference should not be interpreted solely as superior model performance on the 2,000-case dataset; it is also related to the distribution and variability of the target inheritance shares generated by the reference engine. The source-based 500-case dataset therefore provides a complementary and more challenging evaluation setting because it reflects documented jurisprudential configurations rather than only computationally generated cases.

3-8. Discussion of the Results

The consistent superiority of XGBoost across both datasets can be attributed to its ability to model nonlinear interactions among the characteristics of inheritance cases. The distribution of shares is

not determined by a simple linear relationship. It depends on the combination of heirs, their degrees of relationship, the presence or absence of other heirs, exclusion rules, residuary status, and special jurisprudential situations. XGBoost is capable of representing such conditional relationships through successive decision trees and boosting.

Random Forest also obtained strong results, especially on the 2,000-case dataset. Its lower performance compared with XGBoost may indicate that averaging independent trees was less effective than sequential error correction for reproducing the precise numerical outputs of the reference engine. Nevertheless, Random Forest remains a useful model because it is robust, interpretable, and relatively resistant to overfitting.

The MLP neural network performed less effectively in both experiments. This result does not necessarily indicate that neural networks are unsuitable for inheritance prediction. Rather, it may reflect the limited size of the datasets, the discrete nature of inheritance rules, the representation of categorical heir configurations, and the need for more extensive hyperparameter optimization. A larger dataset, improved encoding of the heir structure, class balancing, feature engineering, and systematic tuning of the number of layers, neurons, learning rate, and regularization parameters may improve MLP performance.

The results also show that the second dataset is particularly important for validation because its cases were organized from Maliki jurisprudential sources. However, the target values were still generated by the reference computational engine. Accordingly, the experiment tests the capacity of the models to reproduce the engine's outputs on documented cases, but it does not replace direct validation by experts in Maliki jurisprudence. Future work should include an independently verified test set in which each target share is reviewed by qualified specialists and linked to the exact jurisprudential source and page.

3-9. Limitations

Several limitations should be acknowledged. First, both datasets used target values generated by the reference computational engine. This may produce very high performance if the machine-learning models learn patterns that are closely related to the engine's calculation procedure. Second, the sample size of 500 documented cases remains relatively limited for training a neural network. Third, the results do not include the actual prediction tables, residual plots, or individual-case comparisons; these should be generated from the saved test predictions before final publication. Fourth, MAPE may be sensitive to very small or zero target values and should therefore be interpreted together with MAE and RMSE. Finally, jurisprudential correctness requires independent expert review, particularly in complex cases involving *ʿawl*, *radd*, al-Gharāwayn, al-Akdarīyah, the grandfather and siblings, and inheritance impediments.

4- Conclusion

The independent-test results demonstrate that XGBoost was the most accurate model among the three evaluated algorithms. It achieved the lowest MAE, RMSE, and MAPE values and the highest R2 value on both datasets. Random Forest produced strong but comparatively lower performance, while the MLP neural network showed the greatest prediction errors. These findings support the use of XGBoost as the principal predictive model in the current computational framework.

These findings demonstrate that XGBoost achieved the highest predictive performance among the three models in both experiments, with consistently low error values and high coefficients of determination. The use of two datasets enabled the system to be evaluated from two complementary perspectives: learning from computationally generated cases and testing performance on an independent dataset of documented cases based on Maliki jurisprudence.

Nevertheless, the results should be interpreted as evidence of high agreement with the reference computational engine rather than as definitive proof of jurisprudential validity. The strong performance of XGBoost indicates that the model was highly effective in reproducing the numerical patterns generated by the reference inheritance engine. Additional validation against independently reviewed cases, specialist evaluation, and direct comparison with authoritative Maliki references remain necessary, particularly for complex cases involving ʿ*awl*, *radd*, al-Gharāwayn, al-Akdarīyah, the grandfather with siblings, and inheritance impediments.

The computational framework is extensible and can be improved by increasing the size and diversity of the datasets, adding more documented Maliki cases, incorporating expert-validated labels, testing additional algorithms, and applying explainable-machine-learning techniques. Such improvements may strengthen the system's usefulness for scientific research, the teaching of Islamic inheritance, and the development of digital tools supporting the application of Maliki jurisprudence in Algeria and other countries.

The proposed system should be strengthened through larger datasets, independently reviewed Maliki cases, additional machine-learning models, explainable predictions, and continuous validation by specialists in Islamic inheritance and Maliki jurisprudence. The combination of automated prediction, jurisprudential references, and expert review could contribute to reducing the time and cost of solving inheritance cases while supporting scientific research and the development of reliable digital tools.

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