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PREDICTION OF DIVORCE IN NIGERIA

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Abstract:
Divorce, defined as the legal termination of a marital union, has become increasingly common in contemporary society. Rising divorce rates have been linked to a variety of contributing factors, including infidelity, financial strain, poor communication, and evolving perceptions of gender roles. Understanding these factors is essential for developing appropriate interventions and support strategies. This study investigates the key contributors to marital dissolution and develops predictive models capable of estimating the likelihood of divorce. The research process involved administering structured questionnaires to gather relevant data, followed by comprehensive preprocessing to ensure quality and consistency. The dataset was then divided into three training–testing partitions: 50–50, 66–34, and 80–20. Two machine learning algorithms—Decision Tree and Multilayer Perceptron—were trained and evaluated across these splits. The findings reveal that the Decision Tree model achieved the strongest performance, recording an accuracy of 94% and an F1-score of 0.9469 on the 80–20 split. This surpasses the outcomes obtained from both other partition ratios and the Multilayer Perceptron model. These results indicate that the Decision Tree algorithm offers a robust and reliable approach for predicting divorce based on identified marital factors. The developed predictive models, particularly the Decision Tree, hold practical value for policymakers, social workers, psychologists, therapists, and marriage counselors. By identifying patterns and indicators associated with divorce, stakeholders can design targeted interventions and educational programs. Early awareness and informed guidance may help mitigate the growing prevalence of marital breakdowns and support healthier, more stable relationships.

Keywords: *Accuracy, divorce, decision tree, f1 score, multilayer perceptron.*

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1.0 Introduction

Marriage is widely recognized as one of the most enduring and influential social institutions, typically defined as the legally and socially sanctioned union between a man and a woman. In many cultural contexts—including Nigeria—religion plays a central role in shaping expectations surrounding marriage. Teachings within Christianity and Islam, in particular, emphasize marriage as a sacred covenant, shaping societal perceptions of companionship, procreation, and communal continuity (Adeyemi & Mohammed, 2021; Smith, 2020). Through this cultural and spiritual lens, marriage is not merely a contractual arrangement but a union associated with emotional fulfillment, social stability, and the preservation of lineage.

Although marriage practices vary globally due to cultural traditions, religious doctrines, and customary norms, the fundamental purpose of marriage as a foundation for family structure remains consistent. Nonetheless, marital unions may deteriorate for various reasons, leading couples to pursue divorce. Divorce, defined as the legal dissolution of a marriage, typically involves a series of formal procedures in Nigeria, including petition filing, service of court papers, mediation or negotiation processes, judicial hearings, and the issuance of a final court decree.

Divorce rarely arises from a single cause; rather, it is the outcome of multiple interacting factors. Social, cultural, economic, and interpersonal influences all play critical roles in marital instability. Recent studies show that divorce rates in Nigeria have increased in the last decade, a trend attributed to changing socio-economic realities, evolving cultural values, and shifts in gender roles (Adeyemi & Mohammed, 2021; Smith, 2020). This growing prevalence has far-reaching implications for communities: for example, family disruptions caused by divorce have been linked to issues such as juvenile delinquency, reduced parental supervision, and increased susceptibility to crime, kidnapping, and banditry.

Economic factors remain among the most frequently cited determinants of divorce. Okafor and Ibrahim (2018) reported that financial strain, unequal income distribution between spouses, and persistent economic hardship exert significant pressures on marital stability. Similarly, Adams and Okonkwo (2019), and Afolayan and Okafor (2022) found that increased financial independence and higher educational attainment among women—though generally positive developments—sometimes alter marital dynamics and influence the likelihood of separation.

With advances in data science, predictive modeling has emerged as a promising tool for anticipating marital outcomes. Predictive models offer policymakers, counselors, and couples evidence-based insights into factors contributing to marital breakdown. Ibrahim and Lawal (2022) demonstrated that predictive analytics can reveal early warning signs of marital distress, enabling timely interventions. Likewise, Oladimeji and Adekunle (2023) emphasized that robust predictive models support policy formulation, counseling strategies, and social work practices aimed at reducing divorce rates and strengthening family systems.

Understanding the multifaceted factors contributing to divorce is essential for psychologists, therapists, marriage counselors, and other practitioners. As Adeyemi and Okoro (2020) noted, such insights help professionals design targeted interventions and support frameworks that reduce marital conflict and promote healthier relationships.

This study addresses these gaps by developing and evaluating predictive models for divorce using context-specific data, with particular attention to socio-demographic, cultural, and economic factors. By adopting a predictive and comparative modeling approach, the research moves beyond mere identification of causes and contributes practical, data-driven tools for understanding and anticipating divorce risk.

The choice of machine learning models for predicting divorce in the Nigerian context is informed by the complex, multidimensional, and context-specific nature of marital relationships in the country. Divorce in Nigeria is not driven by a single factor but by the interaction of socio-demographic, cultural, religious, and economic variables such as income instability, educational differences, family interference, religious commitment, gender expectations, and communication patterns. Traditional statistical methods often struggle to capture these non-linear relationships and interactions, thereby limiting their predictive power. Machine learning models, on the other hand, are better suited to uncover hidden patterns within such complex data structures.

The comparative use of multiple machine learning models allows for a more reliable and objective assessment of predictive performance. By evaluating and comparing models using standard performance metrics, the study ensures that the selected model is not only theoretically suitable but also empirically effective for the Nigerian context. This approach strengthens the credibility of the findings and supports evidence-based recommendations.

The adoption of machine learning models is justified by their ability to handle complex relationships, accommodate real-world data limitations, provide interpretable results, and deliver practical predictive insights that align with the socio-cultural and economic realities of Nigeria.

Against this background, the present study seeks to (a) identify and examine key socio-demographic predictors of divorce in Nigeria and (b) develop a machine-learning-based predictive model capable of forecasting divorce among Nigerian couples. The goal is to provide stakeholders—including policymakers, counselors, and researchers—with empirical tools to guide strategies aimed at enhancing marital stability and reducing divorce rates.

2.0 Literature Review

The application of computational and machine learning techniques in the social sciences has expanded considerably in recent years. Within the domain of marital research, scholars have increasingly focused on developing predictive models that help identify potential indicators of divorce.

One major body of research examines demographic and relationship-related variables. These studies typically collect data on age, educational attainment, communication patterns, income levels, duration of marriage, and conflict-management behaviors to determine their influence on marital outcomes. Machine learning algorithms such as Decision Trees, Random Forests, and Support Vector Machines have been employed to predict divorce with notable success (Akinbohun & Adegun, 2023).

The effectiveness of machine learning in predictive tasks is well documented. Although Akinbohun and Adegun's (2023) work focused on diabetes prediction, their use of feature selection techniques such as correlation-based and consistency-based methods demonstrates the analytical strength of machine learning. This methodological approach is adaptable to social issues such as divorce prediction.

Beyond traditional relationship and demographic variables, emerging studies have turned to unconventional data sources. Chen and Smith (2019) explored the predictive potential of social media data, analyzing linguistic patterns, posting behaviors, and interaction styles on platforms such as Facebook and Twitter. Their findings suggest that shifts in online language use and engagement patterns may serve as early indicators of marital distress.

Another innovative approach involves the use of physiological data. Thompson et al. (2020) examined heart rate variability, skin conductance, and facial expressions to identify physiological markers associated with marital conflict. Their research supports the idea that biological responses to stress may predict long-term marital outcomes.

Financial factors have also been established as strong predictors of divorce. Williams and

Johnson (2021) found that financial stress, low economic stability, income disparities, and poor financial management practices significantly increase the likelihood of divorce. These findings align with earlier research linking financial hardship to marital dissatisfaction.

In addition, Ogunleye and Adeniji (2021) highlighted the importance of proactive interventions, including counseling programs and educational initiatives, to mitigate divorce risks. Their work underscored the role of policy-driven preventive measures in supporting couples.

Predictive methodologies relevant to the present study can also be found in other domains. For example, Akinbohun (2020) applied machine learning algorithms such as Decision Trees, Naïve Bayes, and K-Nearest Neighbors—combined with feature selection techniques—to predict hepatitis outcomes, demonstrating the broad applicability of computational modeling in complex decision-making tasks.

Collectively, the literature reveals increasing multidisciplinary interest in the use of predictive models to understand and forecast divorce, highlighting opportunities for improved intervention strategies.

3.0 Research Methodology

3.1 Data Collection and Preprocessing

This study employed a quantitative research approach involving the use of both primary and secondary data. Primary data were collected using structured questionnaires administered to 1,000 divorced individuals across Nigeria. Respondents included both men and women from diverse socio-economic backgrounds. The questionnaire captured variables related to socio-demographic characteristics, communication patterns, emotional factors, financial dynamics, conflict-resolution behaviors, and other marital indicators. The combined dataset contained 54 attributes and 1,000 instances, representing a wide spectrum of divorce predictors. These attributes were categorized into demographic, relationship-related, financial, behavioral, and emotional variables.

3.2 Data Cleaning

Missing values were addressed through appropriate imputation methods—mean substitution for continuous variables and mode substitution for categorical variables. Data cleaning ensured that noise, inconsistencies, and incomplete records did not bias the analysis.

3.3 Normalization

Normalization was performed to scale all variables to a uniform range, typically between 0 and 1. This step was essential because machine learning algorithms—particularly distance-based models—are sensitive to differences in variable scales. Normalization improved algorithm efficiency and minimized distortion in variable contributions.

3.4 System Architecture

The system architecture for the predictive model includes data ingestion, preprocessing, feature selection, model training, and evaluation components. A conceptual overview of the architecture is illustrated in Figure 1.

Tables summarizing the dataset and the normalized version are presented in Tables 1 and 2, respectively.

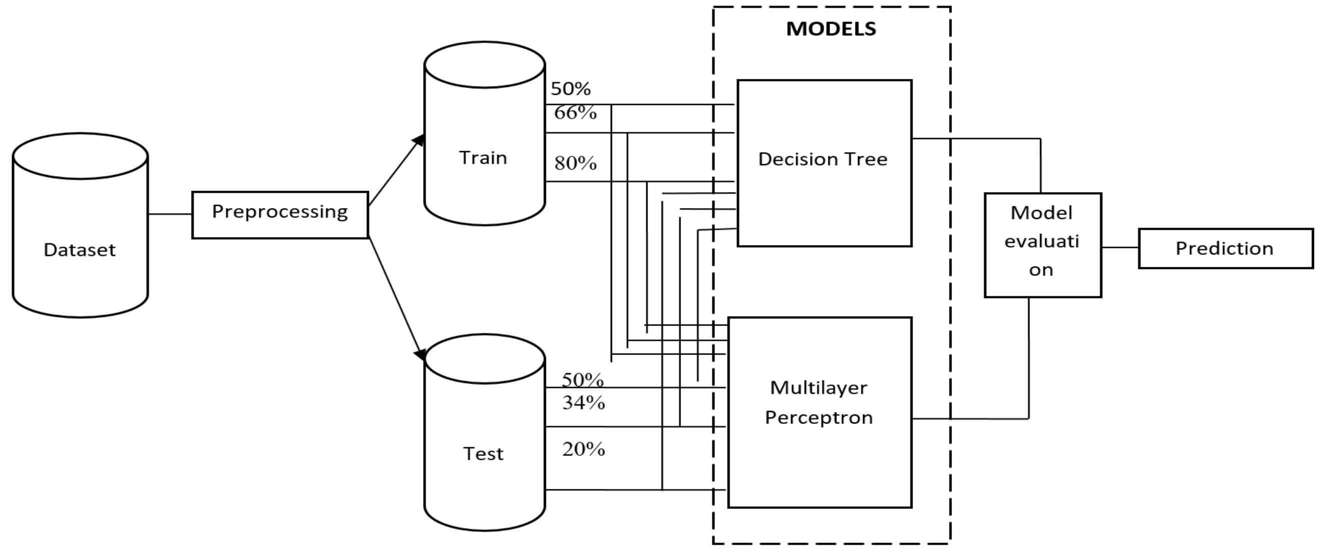


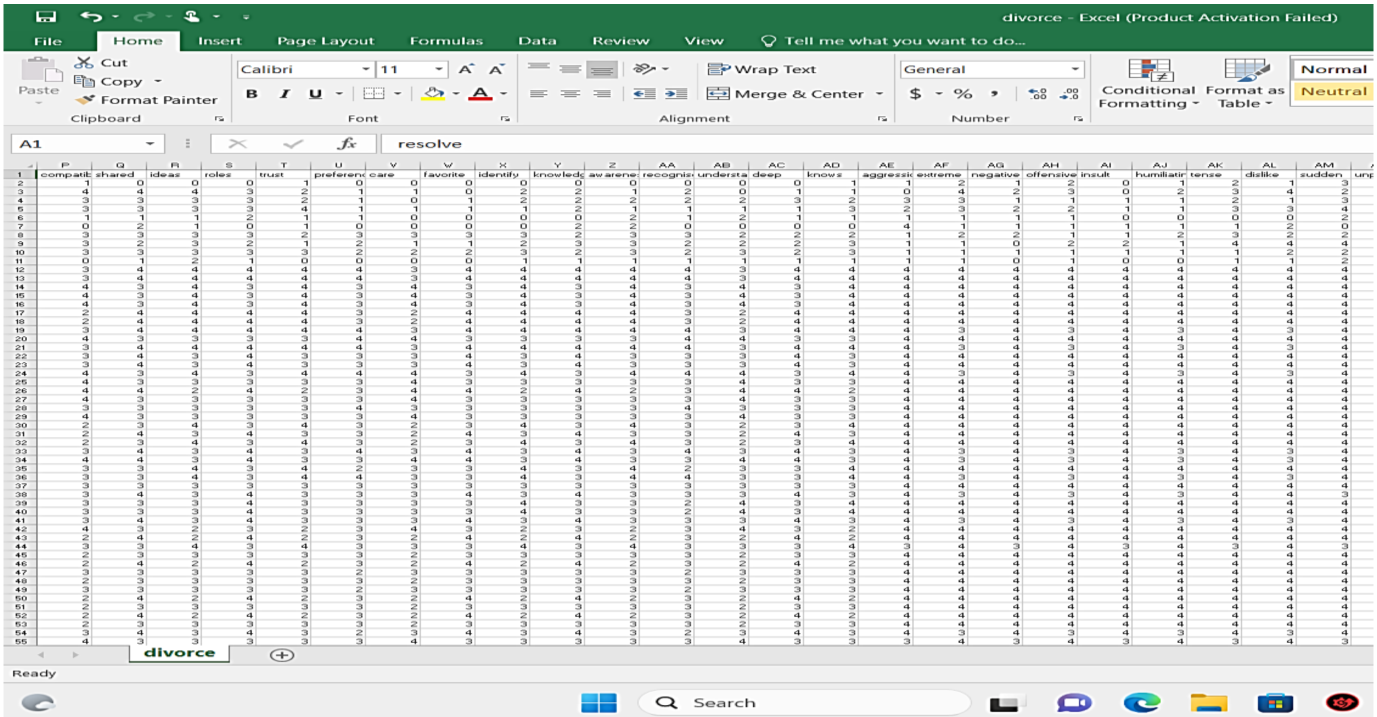
Figure 1: Architecture of prediction of divorce

Table 1: Features of the dataset

Predictors	Descriptions
1. Apology resolves	If one of us apologizes when our discussion deteriorates, the discussion ends.
2. Embrace differences	I know we can ignore our differences, even if things get hard sometimes.
3. Restart discussions	When we need it, we can take our discussions with my spouse from the beginning and correct it.
4. Reach out during arguments	When I discuss with my spouse, to contact him will eventually work.
5. Special time	The time I spent with my wife is special for us.
6. Limited home partnership	We don't have time at home as partners.
7. Strangers at home	We are like two strangers who share the same environment at home rather than family.
8. Enjoy holidays together	I enjoy our holidays with my wife.
9. Travel joy	I enjoy traveling with my wife.
10. Common goals	Most of our goals are common to my spouse.
11. Harmonious future	I think that one day in the future, when I look back, I see that my spouse and I have been in harmony with each other.
12. Shared values, freedom	My spouse and I have similar values in terms of personal freedom.
13. Similar entertainment	My spouse and I have similar sense of entertainment.
14. Common goals for others	Most of our goals for people (children, friends, etc.) are the same.
15. Harmonious dreams	Our dreams with my spouse are similar and harmonious.
16. Love compatibility	We're compatible with my spouse about what love should be.
17. Shared views on happiness	We share the same views about being happy in our life with my spouse
18. Similar marriage ideas	
19. Matching roles in marriage	My spouse and I have similar ideas about how marriage should be

20. Shared trust values	My spouse and I have similar ideas about how roles should be in marriage
21. Understand preferences	My spouse and I have similar values in trust.
22. Care during sickness	I know exactly what my wife likes.
23. Favorite food known	I know how my spouse wants to be taken care of when she/he sick.
24. Identify wife's stress	I know my spouse's favorite food.
25. Knowledge of inner world	I can tell you what kind of stress my spouse is facing in her/his life.
26. Aware of concerns	I have knowledge of my spouse's inner world.
27. Recognize stress sources	I know my spouse's basic anxieties.
28. Know hopes and wishes	I know what my spouse's current sources of stress are.
29. Deep understanding	I know my spouse's hopes and wishes.
30. Know friends and relationships	I know my spouse very well. I know my spouse's friends and their social relationships.
31. Aggression in arguments	I feel aggressive when I argue with my spouse.
32. Use extreme expressions	When discussing with my spouse, I usually use expressions such as 'you always' or 'you never'.
33. Negative statements	I can use negative statements about my spouse's personality during our discussions.
34. Employ offensive language	I can use offensive expressions during our discussions.
35. Insult during discussions	I can insult my spouse during our discussions.
36. Humiliating arguments	I can be humiliating when we discussions.
37. Tense arguments	My discussion with my spouse is not calm.
38. Dislike communication style	I hate my spouse's way of open a subject.
39. Sudden fights	Our discussions often occur suddenly.
40. Unpredictable conflicts	We're just starting a discussion before I know what's going on.
41. Losing calm in discussions	When I talk to my spouse about something, my calm suddenly breaks.
42. Silent during arguments	When I argue with my spouse, ı only go out and I don't say a word.
43. Seek peace	I mostly stay silent to calm the environment a little bit.
44. Consider leaving temporarily	Sometimes I think it's good for me to leave home for a while.
45. Prefer silence over arguing	I'd rather stay silent than discuss with my spouse.
46. Prioritize harmony	Even if I'm right in the discussion, I stay silent to hurt my spouse.
47. Fear losing control	When I discuss with my spouse, I stay silent because I am afraid of not being able to control my anger.
48. Confidence in arguments	I feel right in our discussions.
49. Denial of accusations	I have nothing to do with what I've been accused of.
50. Claim innocence	I'm not actually the one who's guilty about what I'm accused of.
51. Assert rightness	I'm not the one who's wrong about problems at home.
52. Point out inadequacy	I wouldn't hesitate to tell my spouse about her/his inadequacy.
53. Remind of issues	When I discuss, I remind my spouse of her/his inadequacy.
54. Address incompetence	I'm not afraid to tell my spouse about her/his incompetence.

Table 2: Presentation of Dataset in Excel



3.5 Training and Test Data Splitting

A critical step in developing any predictive model is the preparation and separation of data into training and testing subsets. This process ensures that the model is exposed to one portion of the data for learning underlying patterns while another independent portion is reserved to evaluate the model's generalization capability (Jiawei et al., 2011). For this study, the dataset consisting of 1,000 instances was systematically partitioned into three distinct training–test configurations to support robust and comparative performance analysis.

The first configuration employed a 50–50 split, which allocated half of the dataset (500 instances) to the training phase and the remaining half (500 instances) to testing. This balanced approach helps prevent the model from overfitting and provides ample test cases for evaluating generalization performance.

The second configuration utilized a 66–34 split, wherein 66% of the data (660 instances) was used to train the model and 34% (340 instances) was set aside for testing. This proportion is widely adopted in machine-learning research because it offers the model a reasonably large training set while still maintaining a sufficient number of observations for evaluation.

The third configuration implemented an 80–20 split, assigning 80% of the observations (800 instances) to the training set and the remaining 20% (200 instances) to the test set. This approach maximizes the amount of data available for learning, which is beneficial for complex models such as neural networks. However, the relatively smaller test set may increase the variance of the performance estimate.

Using these three complementary splitting strategies allowed the study to assess how the proportion of training data influences the predictive capabilities of the different algorithms. These variations ensure methodological rigor and enable meaningful comparison of model performance across diverse learning conditions.

3.6. Construction of Models

Following data preparation and normalization, the next phase involved constructing predictive models using established supervised machine-learning algorithms. The study employed two widely adopted classification methods—Decision Tree (C4.5) and Multi-Layer Perceptron (MLP) neural networks—due to their proven success in handling structured data and detecting nonlinear relationships (Almeida, 2020; Jiawei et al., 2011). The aim was to develop models capable of accurately predicting divorce outcomes based on socio-demographic and behavioral attributes.

a. Decision Tree Classifier

The Decision Tree model is one of the most suitable and intuitive machine learning techniques for predicting divorce, especially in a socially sensitive context such as marriage. In this study, the Decision Tree is used to classify marriages into likely outcomes (divorce or non-divorce) based on a set of socio-demographic, economic, and behavioral variables collected from respondents.

A Decision Tree works by breaking down a complex decision-making process into a series of simple, logical rules. It begins with a root node, which represents the most influential factor in predicting divorce. This factor is selected based on how well it separates the data into distinct groups using criteria such as information gain or Gini index as presented in equation 1 and 2 (Jiawei et al., 2011). For example, variables like persistent financial stress, lack of communication, or frequent family interference may emerge as dominant splitting factors at the top of the tree. From the root node, the model creates branches that represent possible values or conditions of the selected variable, leading to further nodes and eventually to terminal nodes known as leaf nodes, which represent the final prediction.

One of the key strengths of the Decision Tree model in divorce prediction is its ability to handle both numerical and categorical data without requiring complex data transformation. Variables such as age at marriage, duration of marriage, number of children, income level, educational background, religious commitment, and communication frequency can be directly incorporated into the model. This is particularly important in divorce studies, where many predictors are qualitative in nature and closely tied to human behavior and social norms.

To ensure that the Decision Tree model generalizes well to unseen data, techniques such as pruning are applied. Pruning helps prevent overfitting by removing branches that do not contribute significantly to predictive accuracy. This step is crucial when working with survey-based data, where noise and redundancy are common. Model performance is typically evaluated using metrics such as accuracy, precision, recall, and F1-score to assess how well the tree predicts divorce outcomes.

$$E = - \sum_{i=1}^{n} p_i \, log_2 p_i \qquad (1)$$

Where P_i is the proportion of dataset that belongs to the i-th class
n is number of classes, E is entropy
Information gain computes the difference between entropy before the split and average entropy after the split of the dataset based on given attribute values.

$$\text{Gain} = \text{Info} - \text{Info (Attribute)} \qquad (2)$$

Information gain measures the reduction in entropy achieved after partitioning the dataset based on a selected attribute. Attributes yielding the highest gain are chosen at each split, resulting in a model that divides the data into branches representing decision rules. Decision trees are particularly valuable for their interpretability and ability to uncover relationships in complex datasets.

b. Multi-Layer Perceptron (MLP) Neural Network

The Multi-Layer Perceptron (MLP) neural network is a powerful machine learning model employed in this study to capture the complex and non-linear relationships that influence divorce in Nigeria. Marital breakdown in the Nigerian context is rarely caused by a single factor; rather, it emerges from the interaction of economic pressure, cultural expectations, family influence, communication patterns, religious commitment, and personal behavior. The MLP is well suited to model these intricate interactions, which are often difficult to represent using linear or rule-based techniques.

An MLP consists of three main components: an input layer, one or more hidden layers, and an output layer. In the context of divorce prediction, the input layer receives socio-demographic and behavioral variables such as age at marriage, duration of marriage, income stability, educational disparity, number of children, communication frequency, conflict-resolution style, family interference, and level of religious engagement. Each of these inputs is assigned a weight that reflects its contribution to the prediction process. These weighted inputs are then passed through hidden layers, where activation functions introduce non-linearity and allow the model to learn complex patterns within the data as presented in equation 3 and 4.

The hidden layers play a crucial role in uncovering subtle relationships among variables that may not be immediately obvious. For example, financial stress alone may not lead to divorce, but when combined with poor communication and external family pressure, the risk may significantly increase. The MLP can learn such interactions automatically during training, making it particularly effective for understanding the multifaceted nature of marital instability in Nigeria.

The output layer of the MLP produces the final prediction, typically indicating the likelihood of divorce or marital stability. During training, the model adjusts its weights using a learning process known as backpropagation, which minimizes prediction errors by comparing the model's output with actual outcomes. This iterative process continues until the network achieves an optimal balance between learning accuracy and generalization (Almeida, 2020).

The net input to a neuron is calculated as:

$$net_j = \sum_i w_{ij} \times X_i \quad (3)$$

$$\varphi = \frac{1}{1+e^{-net}} \quad (4)$$

W – weights
X – inputs/attributes

4.0 RESULTS AND DISCUSSION

1. Results of the Classifiers

The predictive experiments were conducted using the Python programming language and its associated machine-learning libraries. Model performance was evaluated using four established classification metrics: Accuracy, Precision, Recall, and F1-Score. These metrics collectively capture the model's ability to correctly classify instances, avoid false positives, retrieve relevant cases, and balance precision with recall.

Each classifier—Decision Tree and MLP—was evaluated under the three training/test split configurations (50–50, 66–34, and 80–20). This approach allowed the study to examine how training set size influences learning efficiency and generalization performance. The performance results for all classifiers under each configuration are summarized in Table 3.

Across the experiments, both models demonstrated strong predictive capacity, although their performance varied depending on the proportion of training data. As expected, larger training sets (e.g., 80–20 split) generally resulted in improved accuracy and more stable performance, particularly for the MLP, which requires substantial data to optimize its network weights. Decision Trees, known for their interpretability and lower data demands, also performed well across all splits but exhibited slightly higher variance in the 50–50 configuration.

These results affirm the potential of machine-learning models to support early detection of marital instability. By identifying key patterns in socio-demographic and behavioral indicators, the developed models can provide actionable insights for counselors, policymakers, and family intervention programs. The findings align with prior research demonstrating the value of computational tools in predicting complex social outcomes (Akinbohun & Adegun, 2023; Thompson et al., 2020).

Table 3: Results of the models

Accuracy		
Training – Testing Data	Decision Tree (DT)	Multilayer Perceptron (MLP)
50/50	92.20%	93.60%
66/34	92.94%	91.76%
80/20	94.00%	92.50%
Precision		
Training – Testing Data	Decision Tree	Multilayer Perceptron
50/50	0.9059	0.9375
66/34	0.9371	0.9116
80/20	0.9469	0.9375
Recall		
Training – Testing Data	Decision Tree	Multilayer Perceptron
50/50	0.9390	0.9292
66/34	0.9266	0.9322
80/20	0.9469	0.9292
F1 Score		
Training – Testing Data	Decision Tree	Multilayer Perceptron
50/50	0.9252	0.9333
66/34	0.9318	0.9218
80/20	0.9469	0.9333

II. Discussion on the Performance Metrics of the Classifiers

The performance of the two classifiers—Decision Tree (C4.5) and Multi-Layer Perceptron (MLP)—was examined using three different training–test configurations to evaluate their predictive capability on divorce outcomes. The assessment relied on widely accepted performance metrics, including Accuracy and F1-Score, which together provide a comprehensive understanding of each classifier’s reliability, precision, and generalization strength.

Accuracy Comparison across Training–Test Splits

Accuracy offers a straightforward evaluation of the proportion of correctly classified instances relative to the total number of instances. Under the 50–50 split, the Decision Tree achieved an accuracy of 92.20%, while the MLP attained a slightly higher accuracy of 93.60%. This indicates that with equal proportions of training and test data, the MLP model demonstrated a marginally superior capacity to generalize and correctly classify divorce outcomes.

However, the trend shifted under the 66–34 split, where the Decision Tree recorded an accuracy of 92.94%, outperforming the MLP, which achieved 91.76%. This outcome suggests that with a larger pool of training data (66%), the Decision Tree benefited more robustly from the available patterns in the dataset than the MLP.

The divergence persisted in the 80–20 split, where the Decision Tree produced an accuracy of 94.00%, compared to 92.50% for the MLP. The 80–20 configuration provided the largest training set, and the Decision Tree leveraged this advantage more effectively than the MLP, achieving its highest accuracy across all configurations.

Collectively, these results indicate that although the MLP performed well under the 50–50 split, the Decision Tree consistently outperformed the MLP in the 66–34 and 80–20 configurations. Overall, based on accuracy, the Decision Tree demonstrated superior predictive stability across the majority of data splitting scenarios.

F1-Score Analysis

The F1-Score, which represents the harmonic mean of Precision and Recall, was employed to further evaluate classifier performance. This metric is particularly useful when dealing with balanced yet sensitive social-science data where both false positives and false negatives carry meaningful implications.

Under the 50–50 split, the MLP recorded an F1-Score of 0.9333, surpassing the Decision Tree, which obtained 0.9252. This finding supports the accuracy-based observation that the MLP initially demonstrated a stronger performance when both training and testing sets were equal.

In the 66–34 split, the Decision Tree achieved an F1-Score of 0.9318, outperforming the MLP, which produced a score of 0.9218. This shows that the Decision Tree maintained better balance between Precision and Recall when more training data was available.

Similarly, in the 80–20 split, the Decision Tree recorded the highest F1-Score of the entire experiment, 0.9469, while the MLP achieved 0.9333. This further reinforces the finding that the Decision Tree benefited substantially from larger training data proportions.

Across all three configurations, the Decision Tree produced the highest overall F1-Score—0.9469 in the 80–20 split—indicating its strong ability to maintain both high accuracy and balanced classification performance.

Overall Comparative Performance

When the three training–test divisions are compared, the Decision Tree consistently demonstrates superior performance, particularly when larger proportions of data are allocated for training. In both accuracy and F1-Score, the highest values were recorded under the 80–20 split, with 94.00% accuracy and an F1-Score of 0.9469. These results suggest that the Decision Tree classifier is more adaptable and more capable of capturing the underlying structure of the dataset, making it the more effective model for predicting divorce in the Nigerian context.

The graphical representation of classifier accuracies (Figure 2) further illustrates the dominance of the Decision Tree across the majority of experimental conditions.

Implications for Policy and Practice

The findings of this study have important implications for stakeholders addressing marital instability in Nigeria. The robust performance of the Decision Tree classifier indicates that predictive modeling can serve as a valuable tool for anticipating marital breakdown. The interpretability of Decision Trees—particularly their ability to present decision rules in human-readable form—makes them especially suitable for practitioners in the social sector.

Government agencies, such as the Ministry of Women Affairs, along with social workers, marriage counselors, psychologists, and therapists, can apply insights from Decision Tree–

based models to identify couples at risk of divorce. This proactive approach can support the design of targeted marital counseling programs, early interventions, and community sensitization initiatives. By leveraging predictive analytics, policymakers can promote healthier marriages, strengthen family structures, and work toward reducing the rising divorce rates in Nigeria.
The prediction of divorce becomes more meaningful and reliable when it is grounded in the socio-cultural realities of Nigeria. Marriage in Nigeria is not merely a union between two individuals; it is a social institution deeply embedded in culture, religion, family networks, and communal expectations. Models that ignore these realities risk oversimplifying marital dynamics and producing predictions that lack relevance in real-life settings. A deeper engagement with Nigerian-specific socio-cultural factors therefore strengthens divorce prediction by ensuring that the variables, interpretations, and outcomes truly reflect lived experiences.

One key socio-cultural factor is the role of extended family involvement in marital affairs. In many Nigerian communities, parents, in-laws, and relatives exert significant influence on marital decisions, conflict resolution, and even separation or divorce. Including variables that capture the intensity and nature of family interference allows predictive models to account for pressures that are often absent in Western-based studies but are critical determinants of marital stability in Nigeria.

Religious beliefs and practices also play a central role in shaping attitudes toward marriage and divorce. Nigeria is a deeply religious society, and faith often influences tolerance, conflict management, gender roles, and the willingness to remain in or exit a troubled marriage. By incorporating measures of religious commitment, denominational expectations, and moral views on divorce, prediction models become more sensitive to the values that guide marital behavior in different religious settings.

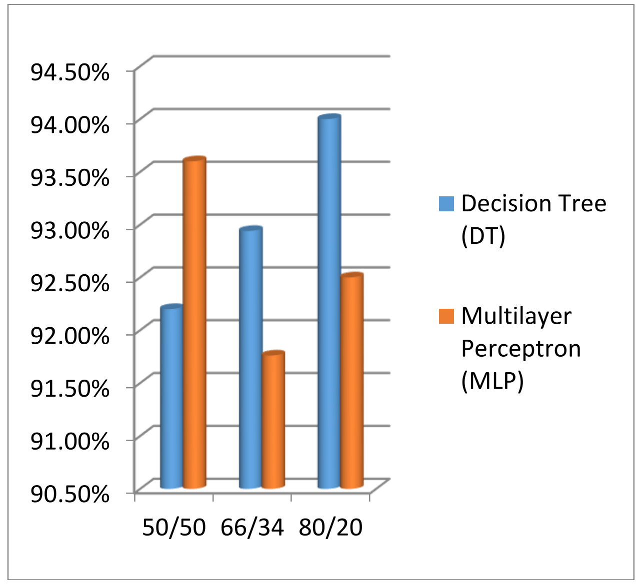


Figure 2: Accuracies of the models (Decision Tree and MLP)

5.0 Conclusion

The findings of this study underscore the relevance and practical value of predictive modeling—particularly the Decision Tree algorithm—in understanding and forecasting divorce outcomes within the Nigerian context. The Decision Tree model demonstrated strong predictive capability, making it a useful analytical tool for professionals engaged in marital counseling, early intervention, and family-related social services. Its interpretability offers practitioners clear insights into the hierarchical structure of risk factors, thereby enhancing their capacity to design targeted and effective marital support programs.

By identifying and analyzing the socio-demographic, cultural, and economic determinants associated with divorce, the study provides a foundation for evidence-based decision-making among policymakers, social workers, therapists, psychologists, and marriage counselors. These insights contribute to the development of informed strategies aimed at strengthening marital relationships, promoting stability within households, and mitigating the broader social consequences of marital dissolution.

The application of the Decision Tree model extends beyond academic analysis; it also offers practical implications for individuals, couples, and families. As a decision-support tool, it can facilitate early identification of marital vulnerabilities, enabling proactive engagement in counseling, conflict resolution, and support services. This predictive approach encourages the adoption of preventive measures that foster healthier and more resilient marital unions.

Furthermore, the study's findings serve as a resource for professionals working in marital and family intervention settings, equipping them with empirically grounded knowledge of the factors contributing to divorce in Nigeria. Ultimately, the incorporation of predictive modeling into marital counseling and policy development provides a pathway for improving intervention strategies, enhancing relationship outcomes, and promoting long-term marital wellbeing across Nigerian communities.

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