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Application of Decision Tree Algorithms for Predicting Trip Purposes in Makurdi, Nigeria

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Keywords

Decision Tree Algorithm

Trip Purpose

Intelligent Transport

Sustainable Transport

Abstract

Decision tree models are versatile and interpretable machine learning algorithms widely used for both classification and regression tasks in transportation planning. This research focuses on analysing the suitability of decision tree algorithms in predicting trip purposes in Makurdi, Nigeria. The methodology involves formalizing household demographic and trip information datasets obtained through an extensive survey process. Modelling and prediction were conducted using Python programming language, and evaluation metrics such as R-squared and Mean Absolute Error (MAE) were used to assess the model's performance. The results indicate that the model performed well, achieving accuracies of 84% and 68% and low MAE values of 0.188 and 0.314 on training and validation data, respectively. These findings suggest the model's reliability for future predictions. The study concludes that the decision tree-based model provides actionable insights for urban planners, transportation engineers, and policymakers to make informed decisions for improving transportation planning and management in Makurdi, Nigeria.

Cite

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1. INTRODUCTION

Urbanization has led to rapid changes in travel behaviour and transportation needs across cities, especially in developing regions (Lyons et al., 2018; Pradhan et al., 2021). Makurdi, Nigeria, is experiencing significant urban expansion, creating challenges for effective transportation planning. Understanding trip purposes, why people travel is critical for optimizing transportation infrastructure and services (Cruz & Sarmento, 2020; Khan et al., 2022). Insights into trip purposes provide a foundation for developing policies that alleviate congestion, improve access, and enhance overall mobility (Gallo & Marinelli, 2020). However, in developing cities like Makurdi, limited access to detailed data complicates traditional approaches to transportation planning, necessitating innovative, data-driven methods. According to Klaus and Wegener (2004), when the demography, socioeconomic status and the spatial configuration of land-use changes, the pattern of travel demand changes, both in the amount and spatial distribution of the demand. For developing travel demand/prediction models, extensive data on current travel patterns is required. Forecasting future travel demand is an important part of the long-term transport planning process for determining strategies for meeting

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future needs. Land-use policies, pricing programs, and the expansion of transportation supply-highway and transit service are examples of such strategies. However, what works in one city may not work in another, necessitating the development of localized travel behavior models or the calibration of current ones to suit cities for efficient and sustainable infrastructure development (Bauriedl & Strüver, 2020; Lovelace, 2021; Cheng et al., 2022; Koumetio Tekouabou et al, 2023; Alghamdi, 2024)

Studies in Nigerian cities, including those focusing on urban centres such as Ilorin, Ibadan, Makurdi, Lagos, Abuja, and Port Harcourt, have often used traditional methods for understanding travel behaviour. These typically involve household surveys, traffic counts, and modal split studies (Akintayo & Adibeli, 2022; Adeke et al., 2018). While these studies provide valuable insights, they often face limitations in terms of data availability and accuracy. As in the case of Makurdi, the availability of structured transportation data in many Nigerian cities is limited, which makes it challenging to implement traditional methods effectively. Similar to the approach in this study, some research has relied on surveys to gather trip characteristics and demographic data (Biala et al., 2024). However, a key difference is that many studies in Nigeria still rely heavily on simple statistical methods, which may not fully capture the complexity of travel demand, especially in rapidly urbanizing areas like Makurdi. The application of machine learning methods, particularly decision trees, as in this study, is relatively novel for Nigerian cities. These methods, as demonstrated in the current study, can provide more accurate predictions and insights, which is especially important in regions where data is scarce and transportation planning needs to be more adaptive to rapid changes in urban dynamics. A few recent studies in Nigerian cities have begun to explore machine learning and AI for transportation modelling and optimization (Biala et al., 2024; Olugbade et al., 2022; Otuoze et al., 2021).

Machine learning algorithms, particularly decision tree models, have demonstrated significant potential in analysing and predicting travel behaviours (Kashifi et al., 2022). Decision trees are widely recognized for their versatility and interpretability, making them ideal for analysing complex datasets in transportation (Nair, 2023; Koushik et al., 2020). Unlike other machine learning algorithms that act as "black boxes," decision trees provide clear insights into the relationships between variables, such as household demographics and trip purposes (Barri et al., 2022). Studies have shown that decision tree algorithms can efficiently model urban travel demand, offering insights critical for urban planning. For instance. An et al. (2022) applied decision tree models to predict peak travel times in dense urban settings, achieving significant accuracy and interpretability in their results. Similarly, Lee et al. (2022) used decision tree regression techniques to analyse small-city travel patterns, highlighting the model’s ability to function effectively in data-scarce environments. To create an intelligent transportation system that can handle traffic congestion and road safety to prevent accidents, artificial intelligence (AI) and machine learning (ML) can be used (Choudhary et al, 2021). According to Bharadiya (2023), machine learning and artificial intelligence (AI) are important in many facets of smart cities, especially when it comes to intelligent transportation systems. Intelligent traffic control, dynamic routing, congestion management, and modeling and simulation are just a few of the applications for these technologies.

Díaz et al. (2018) address the issue of air pollution caused by road traffic in large cities by using an Intelligent Transportation System model based on Complex Event Processing technology and Colored Petri Nets (CPNs). Pulugurta et al. (2013) employed AI techniques for travel demand forecasting. The procedure focused on the mode choice step of the major 4-stages of transport modelling – trip generation, trip distribution, mode choice and traffic assignment. The fuzzy logic technique of AI was used to overcome challenges associated with the traditional regression models as its harness human knowledge as linguistic variables in the form of IF-THEN rules. Also, based on the Victorian Integrated Survey of Travel and Activity, several machine learning algorithms were used to model mode choice decisions in the greater Melbourne area (Richards & Zill, 2019). According to the results of the revealed preference household travel survey, certain machine learning models perform better than the traditional discrete choice model. Sun et al. (2021) contributes to the advancement of travel behavior analysis by showcasing how machine learning algorithms effectively identify trip purposes using mobile signaling data, sampling surveys, and point of interest (POI) data. Further, Zhang and Zhao (2022) discuss how ML models outperform traditional statistical methods in transportation analysis due to their ability to capture complex interdependencies among demographic, socioeconomic, and spatial variables. This underscores the need for adopting advanced ML models in developing cities like Makurdi, where traditional data collection and analysis methods face resource and accuracy constraints. Makurdi presents a unique case for applying decision tree models due to its distinctive urban challenges, including a rapidly growing population and limited transportation infrastructure. The city's reliance on informal transport systems, combined with a lack of structured transportation data, makes predictive modelling essential for effective planning. By leveraging machine learning, this research seeks to fill critical gaps in understanding urban mobility in Makurdi, contributing to both academic discourse and practical urban planning.

2. MATERIAL AND METHOD

2.1. Description of Study Area

Makurdi, Nigeria is the capital city of Benue state situated on latitudes $7^0$37’60’’N to $7^0$50’20’’N and longitudes $8^0$19’30’’E to $8^0$40’20’’E at 93meters above the sea level. The town is primarily drained by the Benue River, which divides it into Makurdi North and South and is connected by two bridges. Residents of Makurdi metropolis, Nigeria work primarily in civil service, business, and agrarian peasantry. The human population of Makurdi metropolis, Nigeria is estimated at 500,797 persons (NPC, 2006); with highest concentration of people in the high level, Wadata and Wurukum districts (Abah, 2012). Location of the study area is as shown in Figure 1.

2.2. Source of Data

Data for the study were sourced through a household questionnaire interview survey carried out in the study area between January 2021 and December 2022. the study area was divided into nine traffic analysis zones (TAZ) based on the geopolitical council wards of the city, which include the following; Bar, Walumayo, Fiide, Modern Market, Wadata/Ankpa, Central South, Clerk/Market, North Bank, North Bank 2. Revealed preference questionnaires was administered to households within Makurdi metropolis to capture information on travel demand based on demographic characteristics of households. The survey considered various data collection methods ranging from the use of web-page (Google form or Survey Monkey and WhatsApp), E-mail and personal interview at home. The Systematic Random Sampling Technique was used in carrying out the travel survey. In using this method, every 3rd household along a street of a study location was selected for the survey. The questionnaire consists of questions which are designed to achieve the socioeconomic and current travel information of respondents. The essential attributes and data type required for the study is as Gender, age, economic status, number of household members, Number of cars available for use by household members, the number and type of driving licenses owned by household members and other household attributes which are the dependent variables while the target variables are the trip purposes such as home-based work (HBW), home-based education (HBE), home-based shopping (HBS), home-based leisure (HBL), non home-based (NHB) and home-based other trip (HBO).

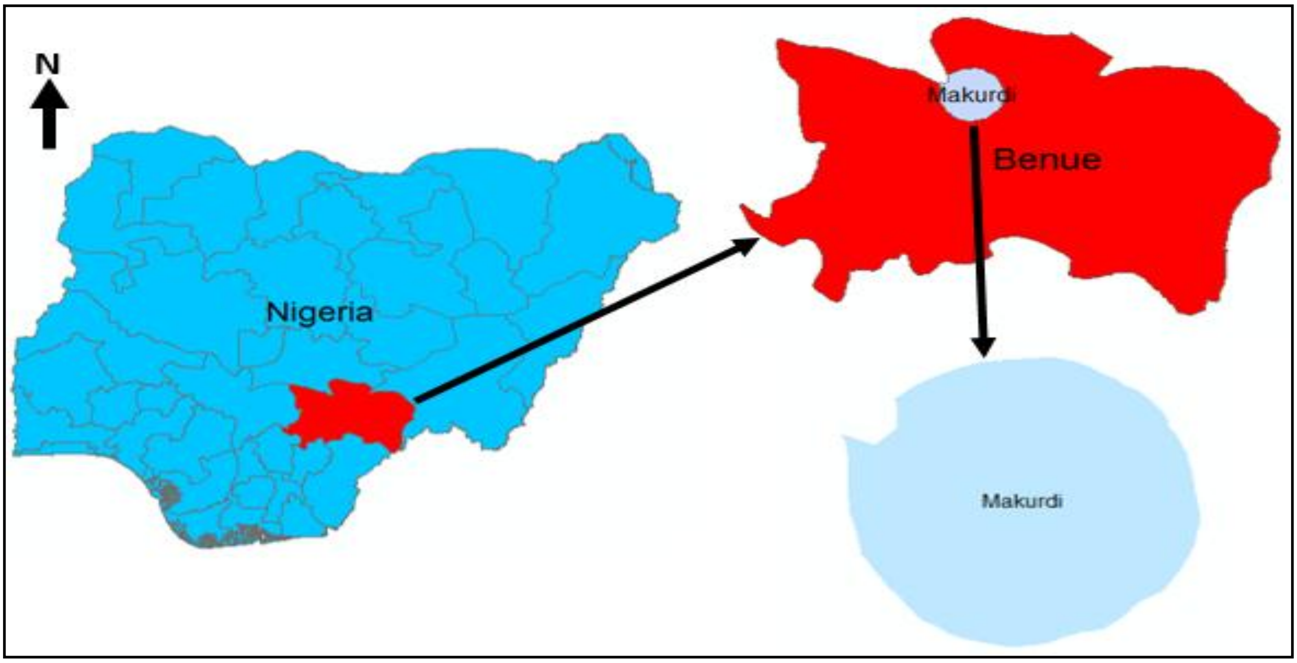

Figure 1. *Location of Study Area*

2.3. Machine Learning (ML) Trip Purpose Predictive Modelling

2.3.1. Decision Tree Model using Python Programming

To analyse the collected data, a Decision Tree Algorithm was employed as the core machine learning (ML) model. The decision tree was chosen due to its ability to handle both categorical and continuous data, which is essential for this study, given the diversity of trip purposes and household characteristics. The model was developed using the Python programming language within the Google Collaboratory environment, which provides a flexible and accessible platform for running and visualising machine learning models. Python's versatility, combined with the power of libraries such as Scikit-learn and Pandas, enabled robust data processing and model training. This model predicted six different trip purposes simultaneously, leveraging household demographic and trip data obtained from the extensive survey. By using a decision tree, the model is able to clearly illustrate the decision-making process for each type of trip purpose, making it easier to interpret the results.

2.3.2. Model Training and Validation

More specifically, a Multioutput decision tree model or regressor was used. Multi Output Regressor is used when there are multiple target variables to predict simultaneously. It extends the concept of simple Decision Tree regression to handle multiple target variables. Each target variable is predicted independently but simultaneously by the model. In this case, we are predicting values for each of 6 trip purposes simultaneously. The dataset used for modelling contains the input parameters for the modelling and prediction processes. The dataset was divided into training and testing sets – 80% for model training and 20% for model testing. The division was achieved using 'train_test_split' function in a Python Library called Sklearn. Other Python Libraries/functions used in the course of the modelling include Pandas, Seaborn, Numpy, Google.colab, and Matplotlib.

2.3.3. Models Evaluation and Visualisations

The performance of the Decision Tree model was evaluated using three key evaluation metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2). These metrics provided insights into the model's accuracy, precision, and explanatory power. In addition to these quantitative measures, visualisations were utilised to gain a deeper understanding of the model's performance. Tools such as feature importance plots were particularly helpful in evaluating how well the model performed for each trip purpose and in highlighting the significance of different input features.

3. RESULTS AND DISCUSSION

3.1. Summary of Dataset for Modelling

From the survey carried out about 1802 households were interviewed and 25 households trip characteristics were collected from each household. 19 of the variables (trip characteristics) were dependent variables while 6 of the variables were the target variables. The travel diary yielded a total of 23102 trips from the households survey. Table 1 shows the data obtained from the household interview survey. The mean and standard deviation of these data are as shown.

The results showed that the average household size is 3.65, mean employment per household is 2.01, mean number of students per household is 1.43, mean number of male and female per household is 2.03 and 1.62, respectively, among other insights that can be seen from the statistics of the data.

Table 1. *Descriptive statistics of dataset obtained from questionnaire survey*

Variables	**mean**	**SD**	**Min.**	**Max.**	**Sum**
Number of household members	3.65	1.28	1	12	6581
Number of Employed household members	2.01	0.8	0	6	3628
Number of vehicles in household	0.22	0.42	0	4	1191
number of household members less than 5 years	0.13	0.38	0	2	229
number of household members > 5 but < 20 years	0.94	0.98	0	5	1692
number of household members > 21 but < 66 years	2.56	0.97	0	8	4607
number of household members > 66 years	0.03	0.19	0	2	56
Number of males in household	2.02	0.92	0	7	3634
number of females in household	1.62	0.81	0	5	2927
Number of students in household	1.43	1.1	0	6	2562
Number of driver’s license holders in household	0.22	0.42	0	4	1186
Total number of household daily trips generated	12.9	4.15	0	32	23102
Number of daily Non-Home-based trips by household (NHB)	0.82	1.08	0	4	1478
Number of Work/Business Trips (HBW)	4.19	1.74	0	12	7494
Number of Shopping Trips (HBS)	3.11	1.68	0	8	5564
Number of School Trips (HBE)	2.77	2.17	0	10	4956
Number of Recreation/social/religious trips (HBL)	0.98	1.3	0	8	1784
Number of Private Car Trips	3.49	1.12	0	9	6296
Number of Keke Trips	0.82	0.34	0	2	1466
Number of Motorcycle Trips	5.56	1.78	0	14	10028
Number of Bus Trips	2.46	0.79	0	6	4423
Number of Walking Trips	0.49	0.19	0	1	890
Number of daily Home-based-other trips by household (HBO)	1.04	1.11	0	4	1856

Source: Survey Data

3.2. Pearson's Correction Analysis

Correlation analysis was done for each pair of variables in the dataset using Python correlation function. Due to the large dimension of the correlation matrix table, a heat map (Figure 2) was used to represent the correlation analysis results for better visualisation. The analysis showed that the correlation coefficients of the overall dataset lie between -0.3 and 1.0. The bar at the right-hand side of the heat map explains the colour code used to represent the correlation coefficients of each pair of variables.

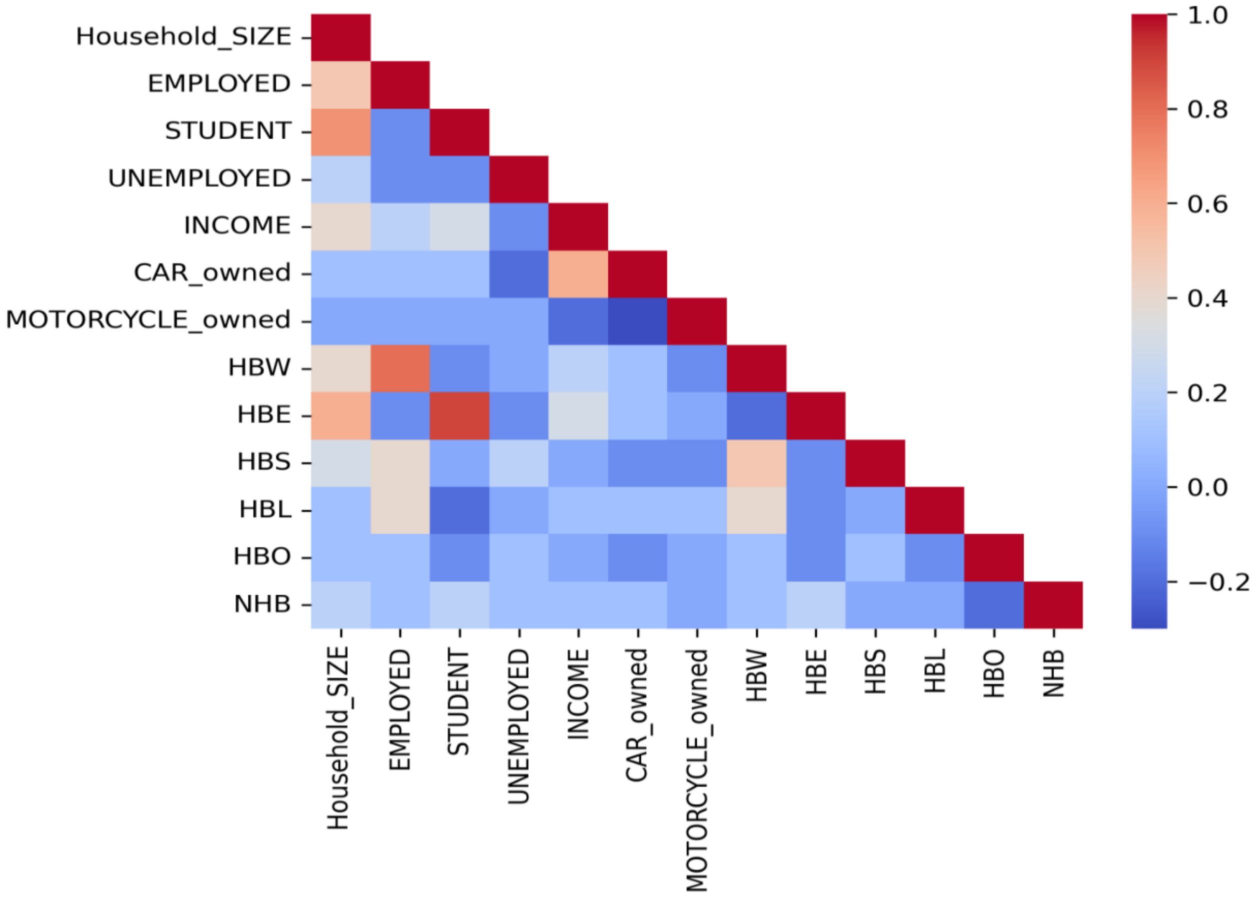

Figure 2: *Heat map of correlation analysis*

3.3. Decision Tree Model

After the data had been pre-processed and split into dependent and independent variables, and split into 80% training and 20% testing datasets, the decision tree model was initiated and built (or trained) on the training data. The optimal decision tree architecture was gotten by evaluating various decision trees based on 'Max_Depth' parameter using R-squared and MAE as accuracy and error metrics, respectively. It was observed that due to the unique characteristics of the data being considered in this study, the accuracy of prediction of the decision tree models increased while the error decreased with increasing value of 'Max_depth' parameter until a Max_depth of 16 (and upward) when the accuracy and error values remained constant or can be said to have converged. This shows that at this point, the number depth is enough to make the most accurate prediction decisions. Hence, a 'max_depth' value of 16 was used in building the decision

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tree model for this study. Figure 3 shows the structure of the first two (depths of 2) of the decision tree model built in this study.

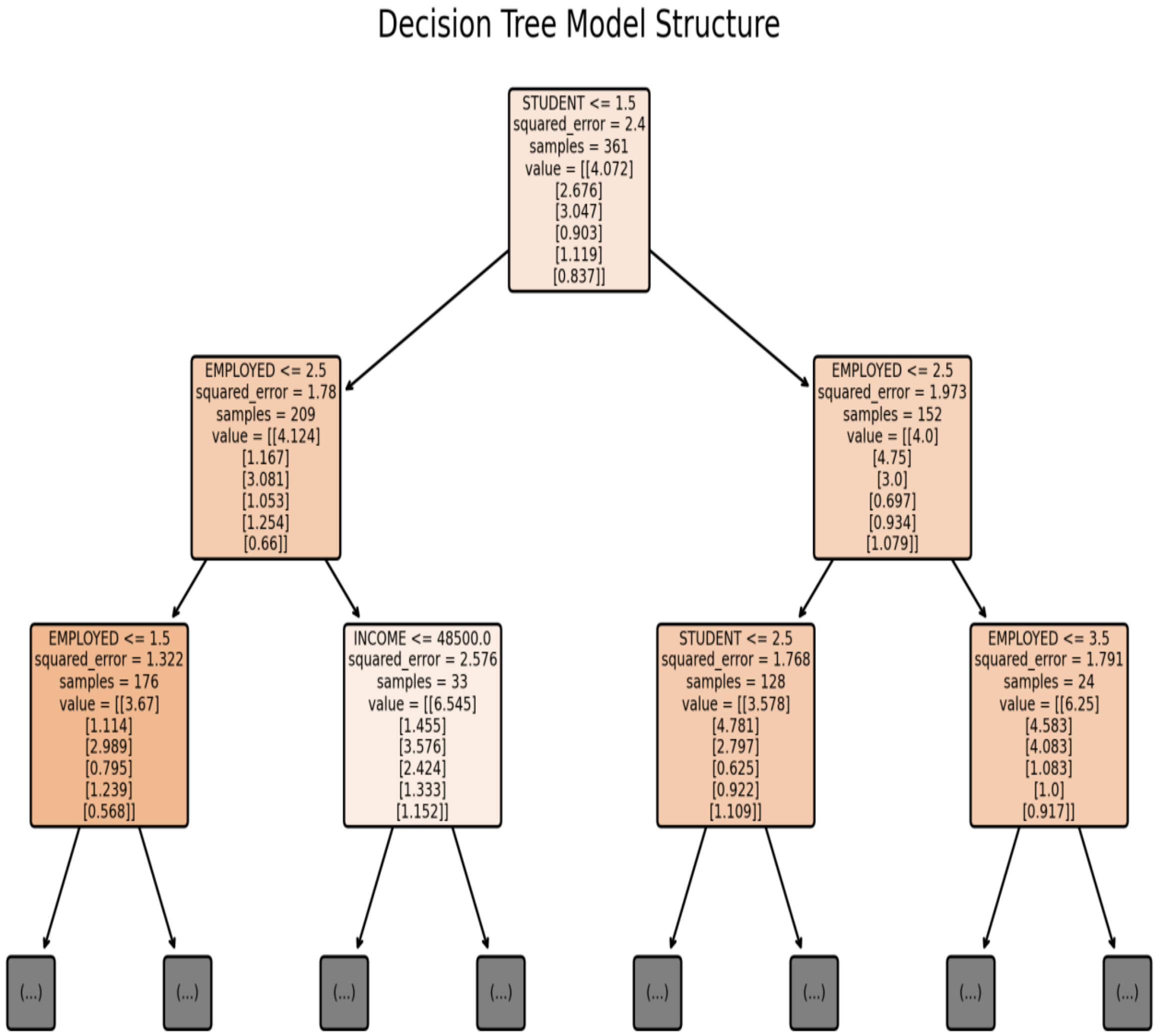

Figure 3. *Decision tree model structure (from the root node to the second level)*

From Figure 3, the mean square error (MSE) on each node represents the minimum value of mean square error that gives the best split on that node while the sample represent the number of training samples that reach that node. The value in each node represents the predictions for all the target variables.

3.4. Model Performance Evaluation and Visualisations

The performance of the trained Decision tree model was then evaluated using R-squared, MAE and MSE. The trained model was also evaluated (validated) by using it to predict previously unseen data (the 20% test data), and the performance measured using the same metrics as shown in Table 2.

Table 2. Performance of the Decision Tree model for Training and Validation

Performance Metrics	Training	Validation
R-squared value	0.841978	0.681508
Mean Absolute Error (MAE)	0.187717	0.313950
Mean Squared Error (MSE)	0.301527	0.615197

These accuracy results show that the Decision Tree model for trip purposes prediction performed satisfactorily well giving an accuracy of 84% and 68%, and MAE values of 0.188 and 0.314, on training and validation data, respectively. This means that the model can be relied upon for future estimations involving trip purpose decisions of households. The application of machine learning, particularly decision tree models, as a method for predicting travel behaviour is consistent with the work of Kashifi et al. (2022) and An et al. (2022), who both demonstrated the success of machine learning algorithms in urban travel demand modelling. However, what differentiates this study is its context in Makurdi, where data availability is limited. Studies like Lee et al. (2022) also used decision trees in data-scarce environments, showing that decision trees can function effectively with limited data. The results of this study (84% accuracy and 68% MAE) are similar to those achieved in these other studies, demonstrating the robustness of decision tree models in predicting trip purpose. Studies like Sun et al. (2021) have shown that machine learning models, particularly decision trees, can perform well in urban mobility analysis, but the exact depth or configuration needed to optimize performance can vary across datasets. In Makurdi, the fact that this depth resulted in a significant drop in MAE suggests that this model was well-suited for the data's specific characteristics.

3.5. Plotting the actual and predicted values for Trip Purposes

In order to further examine the performance of the trained model, the first 20 rows of both the actual dataset and predicted dataset were plotted on a chart as shown in Figure 4.

Examining the plots suggest that the model predicted trip purpose values similar to actual values of trip purposes in the original data. This further confirms the reliability of the Decision Tree model for application in predicting trip purposes.

3.6. Features Importance or Sensitivity Analysis Plot

Feature importance indicates how much each feature contributes to the model's predictions. The higher the importance, the more influential the feature. This doesn't give a traditional mathematical equation, but it provides a sense of which features are more influential in the predictions. The importance scores show how often a feature is used for decision-making in the tree. Feature Importance analysis was carried out using Python programming. The code snippet generates a horizontal bar plot using Seaborn to visualize the feature importance’s. The features are sorted based on their importance, and the corresponding importance values are represented by the lengths of the bars. Figure 5 shows the plot of feature importance analysis for the Decision Tree model for the combined 6 targets (trip purposes). The plot provides a clear visualization of the relative importance of each feature in the Decision Tree model.

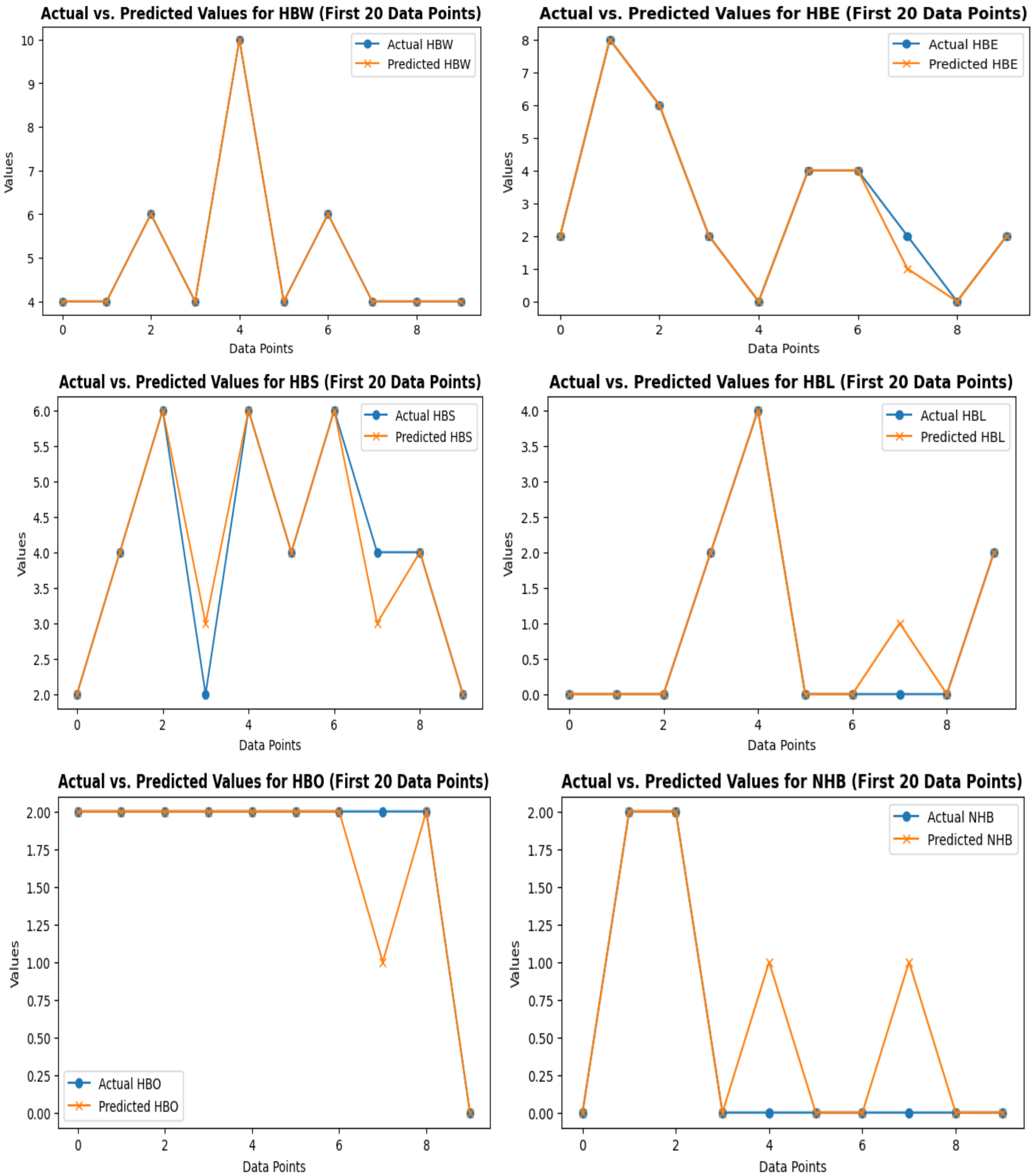

Figure 4. *Actual vs Predicted values for HBW, HBE HBS, HBL, HBO and NHB (first 20 Data Point)*

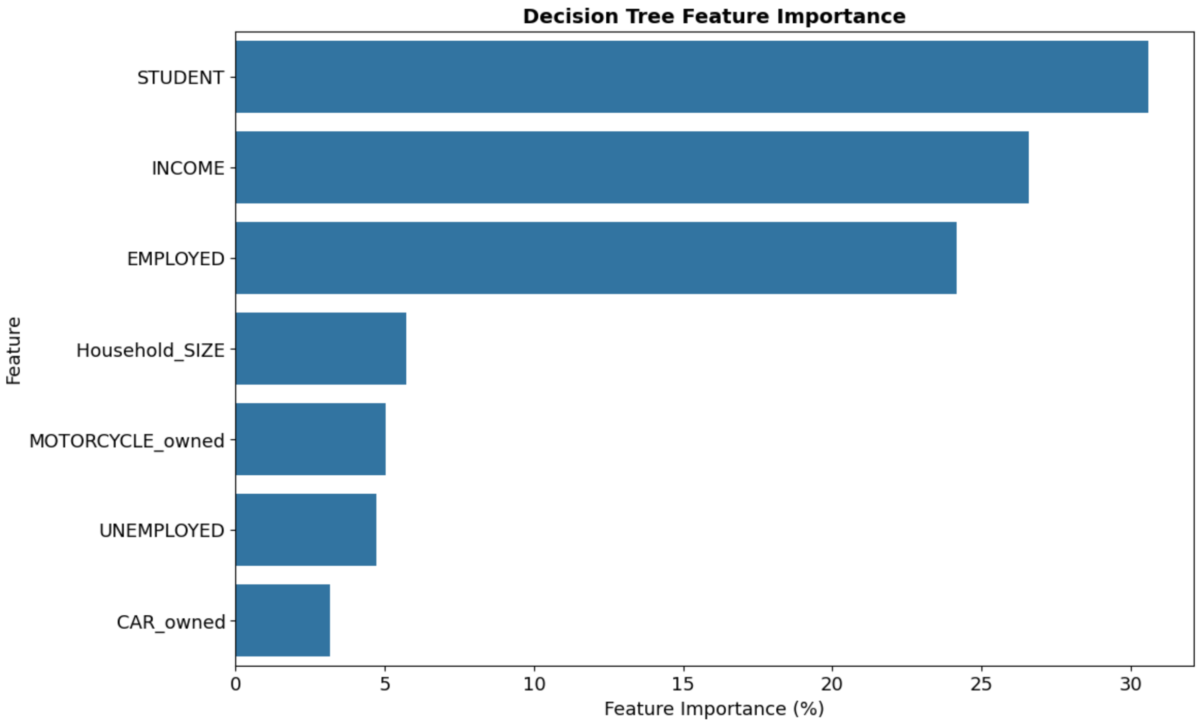

Figure 5. *Feature Importance Analysis for the Decision Tree Model for the Combined 6 Target Trip Purposes*

4. CONCLUSION

This study examined the application of decision tree algorithms for predicting trip purposes in Makurdi, Nigeria. In recent years, machine learning techniques, especially decision trees, have gained prominence in transportation planning due to their ability to manage complex datasets and deliver interpretable results. Decision trees are particularly effective for modelling trip purposes as they can capture non-linear relationships between various input factors, making them ideal for understanding the diverse influences on travel behaviour in Makurdi. The main objective of this research was to evaluate the performance of the decision tree algorithm in accurately predicting trip purposes based on demographic and travel data. The application of this algorithm offers significant potential for enhancing transportation planning and management in Makurdi, contributing to more efficient and sustainable urban mobility systems. The model's success in predicting trip purposes provides valuable insights that can guide the development of improved transportation systems in the city.

The study found that the decision tree algorithm performed exceptionally well in predicting trip purposes, with accuracy rates of 84% and 68% on the training and validation datasets, respectively, alongside low Mean Absolute Error (MAE) values of 0.188 and 0.314. These results confirm the algorithm’s robustness and reliability in making future predictions regarding household travel decisions. Visualizing the predictions of the model versus the actual dataset shows a close similarity between the prediction curve and actual data curve, further corroborating the model’s reliability. The feature importance analysis of the Decision Tree model for predicting trip purposes reveals that attributes such as "STUDENT," "INCOME," and "EMPLOYED" play crucial roles, contributing approximately 30.60%, 26.59%, and 24.17% respectively. Conversely, factors like

"Household_SIZE," "MOTORCYCLE_owned," "UNEMPLOYED," and "CAR_owned" have lower predictive significance, ranging from 3.17% to 5.73%. Overall, demographic and socioeconomic factors, notably student status, income, and employment, greatly influence trip purpose predictions. Decision tree algorithm offers several advantages for trip purpose prediction. It is easy to interpret, allowing transportation planners to understand the factors that influence trip purposes. By embracing digital innovation, cities can create more efficient, sustainable, and resilient transportation systems that meet the needs of a rapidly urbanizing world.

AUTHOR CONTRIBUTIONS

Conceptualization, Emmanuel Okechukwu Nwafor and Dr. Folake Olubunmi Akintayo; methodology, Emmanuel Okechukwu Nwafor and Dr. Folake Olubunmi Akintayo.; fieldwork, Emmanuel Okechukwu Nwafor; software, Emmanuel Okechukwu Nwafor; title, Emmanuel Okechukwu Nwafor and Dr. Folake Olubunmi Akintayo; validation, Emmanuel Okechukwu Nwafor and Dr. Folake Olubunmi Akintayo; laboratory work, Emmanuel Okechukwu Nwafor and Dr. Folake Olubunmi Akintayo; formal analysis, Emmanuel Okechukwu Nwafor and Dr. Folake Olubunmi Akintayo; research, Emmanuel Okechukwu Nwafor and Dr. Folake Olubunmi Akintayo; sources, Emmanuel Okechukwu Nwafor and Dr. Folake Olubunmi Akintayo; data curation, Emmanuel Okechukwu Nwafor and Dr. Folake Olubunmi Akintayo; manuscript-original draft Emmanuel Okechukwu Nwafor; manuscript-review and editing, Dr. Folake Olubunmi Akintayo; visualization, Emmanuel Okechukwu Nwafor and Dr. Folake Olubunmi Akintayo; supervision, Dr. Folake Olubunmi Akintayo; project management, Emmanuel Okechukwu Nwafor and Dr. Folake Olubunmi Akintayo; funding, Emmanuel Okechukwu Nwafor and Dr. Folake Olubunmi Akintayo. All authors have read and legally accepted the final version of the article published in the journal.

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CONFLICT OF INTEREST

The authors declare no conflict of interest

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