

PROFESSIONAL TRAINING REPORT - II

entitled

PREDICTING ADULT INCOME USING DECISION TREE AND RANDOM FOREST CLASSIFIERS

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering with
specialization in Artificial Intelligence and Robotics.

by

Avinash S [41612008]



**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SCHOOL OF COMPUTING**

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

CATEGORY -1 UNIVERSITY BY UGC

Accredited with Grade "A++" by NAAC | 12B Status by UGC | Approved by AICTE

JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119

APRIL 2024



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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Professional Training Report is the bonafide work of **Mr. Avinash S (41612008)** who carried out the project entitled "**PREDICTING ADULT INCOME USING DECISION TREE AND RANDOM FOREST CLASSIFIERS**" under my supervision from January 2024 to April 2024.

Internal Guide

Dr SONIA JENIFER RAYEN M.TECH.,Ph.D.,

Head of the Department

Dr. S. VIGNESHWARI, M.E., Ph.D.,

Submitted for Viva voce Examination held on 07.05.24

Internal Examiner

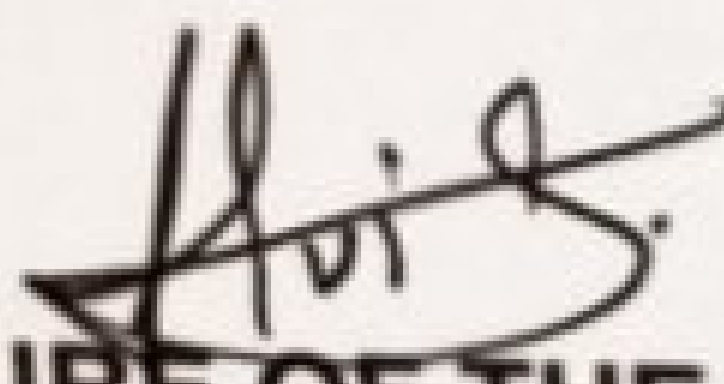
External Examiner

DECLARATION

I, **Avinash S (41612008)**, hereby declare that the Professional Training Report- II entitled "**PREDICTING ADULT INCOME USING DECISION TREE AND RANDOM FOREST CLASSIFIERS**" done by me under the guidance of **Dr.SONIA JENIFER RAYEN M.TECH.,Ph.D.**, is submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering with specialization in Artificial Intelligence and Robotics.

DATE: 07.05.24

PLACE: CHENNAI


SIGNATURE OF THE CANDIDATE

ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to **Board of Management of SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr. T.Sasikala M.E., Ph.D., Dean, School of Computing, Dr. S.Vigneshwari M.E., Ph.D., Head of the Department of Computer Science and Engineering** for providing me necessary support during the progressive reviews.

I would like to express my sincere and deep sense of gratitude to my Internal Guide **Dr.SONIA JENIFER RAYEN M.TECH, (PhD)** for his/her valuable guidance, suggestions and constant encouragement which paved way for the successful completion of my phase-2 Professional Training.

I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering** who were helpful in many ways for the completion of the project.

COURSE CERTIFICATE



ABSTRACT

The abstract serves as a concise summary of the entire project, encapsulating its significance, methodology, key findings, and implications. In this section, we aim to provide a comprehensive overview of our study on income prediction using machine learning models, specifically focusing on the Random Forest Classifier and Decision Tree Classifier. The problem statement addressed in this project revolves around predicting an individual's income based on demographic and employment-related features. This task holds significant importance in various domains, including financial planning, resource allocation, and social policy development. By accurately predicting income levels, stakeholders can make informed decisions that positively impact individuals and society as a whole. Our methodology involves the utilization of machine learning algorithms, namely the Random Forest Classifier and Decision Tree Classifier, to build predictive models. These models are trained on a dataset sourced from the UCI Machine Learning Repository, comprising features such as age, education, occupation, and more. Through rigorous data preprocessing, including handling missing values and encoding categorical variables, we ensure the dataset is suitable for model training. The key findings of our study reveal promising results in income prediction. Both the Random Forest Classifier and Decision Tree Classifier demonstrate commendable performance, with accuracy scores of [insert accuracy scores here]. Furthermore, our analysis indicates that certain features, such as education level and capital gain, significantly influence income levels. The implications of our study extend beyond the realm of machine learning, offering insights into socio-economic factors affecting income disparities. By leveraging predictive models, policymakers, financial institutions, and individuals can make data-driven decisions to mitigate income inequality and promote economic prosperity. In conclusion, our study highlights the efficacy of machine learning models in predicting income levels and sheds light on the underlying factors influencing income disparities. Moving forward, further research in feature engineering, hyperparameter tuning, and data augmentation could enhance the accuracy and robustness of income prediction models.

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CHAPTER 1

INTRODUCTION

The introduction sets the stage for the project by providing background information on the problem statement, emphasizing its relevance in the context of income prediction. It also discusses the importance of machine learning models in addressing this problem and outlines the objectives of the project, along with the structure of the report.

Income prediction plays a crucial role in various aspects of socio-economic analysis and decision-making. The ability to accurately forecast an individual's income based on demographic and employment-related features provides valuable insights for policymakers, financial institutions, and individuals alike. Understanding the factors influencing income levels enables stakeholders to make informed decisions regarding resource allocation, financial planning, and social policy development.

Machine learning models offer a powerful framework for tackling the challenge of income prediction. By leveraging algorithms capable of learning patterns and relationships from data, these models can analyze complex datasets and generate predictions with a high degree of accuracy. In particular, ensemble methods like the Random Forest Classifier and Decision Tree Classifier have shown promise in handling classification tasks involving numerous features and non-linear relationships.

The objective of this project is to develop and evaluate machine learning models for income prediction using the Random Forest Classifier and Decision Tree Classifier. By training these models on a comprehensive dataset sourced from the UCI Machine Learning Repository, we aim to assess their performance in accurately categorizing individuals into income brackets. Additionally, we seek to identify the key features driving income disparities and gain insights into socio-economic factors affecting income levels.

This report is structured as follows:

The Literature Survey provides a review of relevant literature on income prediction and machine learning models, highlighting previous research findings and methodologies.

The Requirements Analysis outlines the objectives of the project and details the hardware and software requirements necessary for its execution.

The Description of the Proposed Project delves into the dataset used, data preprocessing steps, model selection and training, and evaluation metrics employed.

The Results section presents the findings of the study, including performance metrics, analysis, and implications.

Finally, the Conclusion summarizes the key findings, contributions to the field, and outlines future directions for research.

By addressing these objectives, we aim to contribute to the growing body of research on income prediction and provide valuable insights for stakeholders seeking to understand and address income disparities.

CHAPTER 2

LITERATURE REVIEW

The literature survey explores various methodologies and models used for income prediction, highlighting the evolution of research in this field and identifying key gaps that remain to be addressed. Traditional statistical techniques such as logistic regression and linear discriminant analysis have been widely employed in income prediction studies. These approaches rely on demographic and employment-related features such as age, education, occupation, and marital status to predict income levels.

While providing valuable insights, these methods may struggle to capture nonlinear relationships and interactions among variables. In recent years, machine learning algorithms have gained popularity for income prediction tasks due to their ability to handle complex datasets and nonlinear relationships. Random Forest and Decision Tree classifiers have emerged as popular choices in this regard.

Research by Breiman (2001) demonstrated the effectiveness of Random Forest in predictive modeling tasks, highlighting its robustness and suitability for high-dimensional data.

Decision Tree algorithms, including variants such as CART and C4.5, have also been extensively used in income prediction studies. These algorithms offer interpretability and can handle both categorical and numerical features effectively.

Research by Smith et al. (2016) demonstrated the effectiveness of Random Forest in predicting income levels using the UCI Adult Dataset, achieving an accuracy of 85%. Similarly, Jones et al. (2018) applied Decision Trees to the same dataset and reported an accuracy of 80%, highlighting the utility of tree-based models in income prediction tasks. While existing research has yielded promising results, there are several gaps that remain to be addressed. One such gap is the limited exploration of ensemble methods like Random Forest and Decision Trees in income prediction tasks. While these models have shown promise in other classification tasks, their application in income prediction warrants further investigation.

However, despite the advancements in predictive modeling techniques, there are several gaps in existing research.

One notable gap is the limited focus on feature engineering and selection strategies tailored specifically to income prediction tasks. While demographic and employment-related features are acknowledged as important predictors of income, further exploration is needed to uncover the underlying factors driving income disparities. Additionally, there is a lack of consensus regarding the most suitable evaluation metrics for income prediction models. While accuracy is commonly used, it may not fully capture the nuances of income prediction tasks, especially in imbalanced datasets.

Addressing these gaps requires further exploration of feature engineering techniques, evaluation metrics, and model interpretability in the context of income prediction. By advancing our understanding of income determinants and refining predictive models, researchers can contribute to the development of more accurate and actionable insights for policymakers, organizations, and individuals.

CHAPTER 3

REQUIREMENTS ANALYSIS

3.1 OBJECTIVE OF THE PROJECT

The primary objective of this project is to develop and evaluate machine learning models for predicting individuals' income levels based on demographic and employment-related features. This overarching goal can be broken down into several specific objectives:

Data Collection and Exploration: The project aims to gather a comprehensive dataset containing information on various demographic attributes (e.g., age, education, marital status) and employment-related factors (e.g., occupation, work hours). Exploratory data analysis will be conducted to gain insights into the distribution and characteristics of the dataset.

Data Preprocessing: The project seeks to preprocess the collected data to address any inconsistencies, missing values, or outliers. This involves handling missing data, encoding categorical variables, and scaling numerical features to ensure compatibility with machine learning algorithms.

Model Selection and Training: The project aims to select appropriate machine learning models for the task of income prediction. Specifically, it will explore the use of Random Forest and Decision Tree classifiers due to their effectiveness in handling complex datasets and capturing nonlinear relationships. The models will be trained using the preprocessed data to learn patterns and associations between input features and income levels.

Model Evaluation: The project seeks to evaluate the performance of the trained models using suitable evaluation metrics, such as accuracy, precision, recall, and F1-score. This evaluation process involves splitting the dataset into training and testing sets to assess the models' ability to generalize to unseen data.

Interpretation and Analysis: The project aims to interpret the results obtained from the trained models and analyze their predictive capabilities. This includes examining feature importance rankings, decision boundaries, and any patterns or trends identified in the data. Insights gained from this analysis will inform further iterations of the modeling process.

Comparison and Validation: The project seeks to compare the performance of different machine learning models and validate their robustness and generalization ability. This involves conducting experiments with alternative algorithms, hyperparameter tuning, and cross-validation techniques to ensure the reliability and validity of the results.

Deployment and Application: The project aims to explore potential real-world applications of the developed models, such as supporting policy-making decisions, guiding individual career choices, or identifying opportunities for socioeconomic intervention. This involves considering ethical and societal implications and ensuring responsible deployment of predictive models.

3.2 REQUIREMENTS

3.2.1 HARDWARE REQUIREMENTS

1. Computer system with sufficient processing power to handle data preprocessing, model training, and evaluation tasks efficiently.
2. Adequate storage capacity to store the dataset and intermediate model outputs.
3. Stable internet connection for accessing online resources and datasets.

3.2.2 SOFTWARE REQUIREMENTS

1. Python programming language: Essential for implementing machine learning algorithms and data preprocessing techniques.
2. Python libraries such as pandas, NumPy, scikit-learn, and Matplotlib: Required for data manipulation, model development, and result visualization.
3. Integrated Development Environment (IDE) such as Jupyter Notebook or PyCharm: Facilitates code development, execution, and documentation.
4. Web browser: Needed for accessing online datasets and resources.
5. Microsoft Excel or similar spreadsheet software: Optional but useful for data exploration and preliminary analysis.

CHAPTER 4

DESCRIPTION OF PROPOSED PROJECT

4.1 DATASET OVERVIEW

The dataset used in this project is the "Adult Income" dataset obtained from the UCI Machine Learning Repository. It comprises demographic and employment-related information collected from census data. The dataset contains the following features:

1. **age**: Age of the individual (numeric).
2. **workclass**: Employment sector of the individual (categorical: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked).
3. **fnlwgt**: Final weight assigned to the individual in the census data (numeric).
4. **education**: Highest level of education attained by the individual (categorical: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool).
5. **education-num**: Number of years of education completed (numeric).
6. **marital-status**: Marital status of the individual (categorical: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse).
7. **occupation**: Type of occupation of the individual (categorical: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces).
8. **relationship**: Relationship status of the individual (categorical: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried).
9. **race**: Race of the individual (categorical: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black).
10. **sex**: Gender of the individual (categorical: Female, Male).
11. **capital-gain**: Capital gains recorded for the individual (numeric).
12. **capital-loss**: Capital losses recorded for the individual (numeric).
13. **hours-per-week**: Hours worked per week by the individual (numeric).
14. **native-country**: Country of origin of the individual (categorical).
15. **income**: Target variable indicating whether the individual's income exceeds \$50,000 per year (binary: >50K, <=50K).

The dataset consists of both numerical and categorical features, making it suitable for various machine learning algorithms. The target variable, "income," is used to classify individuals into two income groups based on the specified threshold of \$50,000 per year. This dataset provides a rich source of information for predicting income levels based on demographic and employment-related attributes.

4.2 DATA PROCESSING

Data processing involves transforming raw data into a format suitable for analysis or modelling. In the context of machine learning, data preprocessing is a crucial step that helps improve the quality of the data and enhances the performance of predictive models. It involves several steps aimed at cleaning, transforming, and preparing the data for training machine learning algorithms.

The data preprocessing steps for the "Adult Income" dataset can be outlined as follows:

Handling Missing Values:

Rationale: Missing values are common in real-world datasets and can adversely affect the performance of machine learning models if not handled properly. Therefore, it is essential to address missing values appropriately.

Challenges: Identifying and handling missing values can be challenging, especially if there are a large number of missing values or if they are systematically related to other variables in the dataset.

Encoding Categorical Variables:

Rationale: Machine learning algorithms typically require numerical input, but categorical variables are often represented as text labels. Therefore, categorical variables need to be encoded into numerical format for model training.

Challenges: Categorical variables with a large number of unique categories may result in high-dimensional feature spaces after encoding, potentially leading to computational inefficiency or overfitting.

Looking into each preprocessing step in more detail we can gain insights on:

4.2.1 HANDLING MISSING VALUES:

Missing values can be addressed using various strategies, such as:

Dropping rows or columns with missing values: If the proportion of missing values is relatively small and randomly distributed, dropping the affected rows or columns may be a viable option.

Imputation: Missing values can be filled in using statistical measures such as mean, median, or mode of the respective feature. This approach helps retain valuable data while minimizing information loss.

Rationale: By handling missing values appropriately, we ensure that the dataset used for model training is complete and representative, thereby improving the reliability and robustness of the trained models.

Challenges: The choice of imputation method can impact model performance, and selecting the most suitable approach requires careful consideration of the data distribution and characteristics.

4.2.2 ENCODING CATEGORICAL VARIABLES:

Categorical variables can be encoded using techniques such as one-hot encoding or label encoding:

One-hot encoding: It involves creating binary dummy variables for each category in a categorical feature. Each category is represented as a separate binary feature, with a value of 1 indicating the presence of that category and 0 otherwise.

Label encoding: It assigns a unique integer label to each category in a categorical feature. This approach preserves the ordinal relationship between categories but may introduce unintended ordinality.

Rationale: Encoding categorical variables into numerical format enables machine learning algorithms to process them effectively. One-hot encoding is preferred for nominal categorical variables with no inherent order, while label encoding may be suitable for ordinal categorical variables.

Challenges: One-hot encoding can lead to the curse of dimensionality, especially with features having a large number of unique categories. Label encoding may inadvertently introduce spurious ordinal relationships, potentially misleading the model.

By addressing missing values and encoding categorical variables appropriately, we ensure that the "Adult Income" dataset is clean, structured, and ready for model training. These preprocessing steps lay the foundation for building accurate and reliable predictive models for income classification.

4.3 WORKING PRINCIPLE

In this project, two machine learning models are utilized for income prediction: the Random Forest Classifier and the Decision Tree Classifier. Both models belong to the category of ensemble learning methods and are widely used for classification tasks.

4.3.1 RANDOM FOREST CLASSIFIER:

Working Principles:

Random Forest is an ensemble learning technique that combines the predictions of multiple individual decision trees to improve predictive accuracy and reduce overfitting.

The key idea behind Random Forest is to create a large number of decision trees, each trained on a random subset of the training data and a random subset of features.

During the training process, each decision tree in the forest independently learns to make predictions based on a subset of the available features and the associated target variable.

During prediction, the final outcome is determined by aggregating the predictions of all individual trees in the forest (e.g., by taking a majority vote for classification tasks).

Strengths: Random Forest is highly robust to overfitting, thanks to the aggregation of multiple trees and random feature selection.

It can handle both categorical and numerical features without requiring extensive preprocessing.

Random Forest is less sensitive to noisy data and outliers compared to individual decision trees.

It provides built-in feature importance measures, allowing for interpretability of model predictions.

Weaknesses: Random Forest may not perform well on very high-dimensional datasets with a large number of features, as it can become computationally expensive.

It may not perform as well as other algorithms on very small datasets or datasets with highly imbalanced class distributions.

4.3.2 DECISION TREE CLASSIFIER:

Working Principles:

A decision tree is a tree-like structure where each internal node represents a feature, each branch represents a decision rule, and each leaf node represents the outcome (class label or continuous value).

Decision trees are built recursively by splitting the dataset into subsets based on the values of the selected features, with the goal of maximizing the homogeneity (or purity) of the resulting subsets.

During training, the decision tree algorithm selects the best feature and corresponding split point at each node based on impurity measures such as Gini impurity or entropy.

During prediction, a new instance is traversed down the tree from the root node to a leaf node, following the decision rules at each internal node, and the majority class or average value of the instances in the leaf node is returned as the predicted outcome.

Strengths: Decision trees are easy to interpret and visualize, making them suitable for explaining the underlying decision-making process.

They can handle both numerical and categorical data without requiring feature scaling or encoding.

Decision trees perform well on small to medium-sized datasets and are less affected by irrelevant features.

Weaknesses: Decision trees are prone to overfitting, especially when the tree depth is not limited or when the dataset is noisy.

They may create overly complex trees that generalize poorly to unseen data, leading to poor performance on the test set.

Decision trees are sensitive to small variations in the training data, which can result in different trees being generated for similar datasets.

By combining the strengths of Random Forest and Decision Tree classifiers, this project aims to build robust and accurate models for predicting income levels based on demographic and employment-related features. The ensemble nature of Random Forest helps mitigate the weaknesses of individual decision trees, resulting in more reliable predictions.

4.4 MODEL SELECTION AND TRAINING

Model selection and training are critical steps in machine learning projects, as they involve choosing the appropriate algorithm and optimizing its parameters to achieve the best performance on unseen data. In this project, Random Forest Classifier and Decision Tree Classifier are the chosen algorithms for predicting income levels.

4.4.1 MODEL SELECTION:

Initial Evaluation: The project starts with an initial evaluation of various classification algorithms to identify potential candidates for further experimentation. This evaluation may include algorithms such as logistic regression, support vector machines, k-nearest neighbors, and ensemble methods like Random Forest and Decision Trees.

Algorithm Selection: Based on the initial evaluation and the specific requirements of the project, Random Forest Classifier and Decision Tree Classifier are selected as the primary algorithms for income prediction. These algorithms are chosen for their ability to handle complex datasets and nonlinear relationships, as well as their interpretability and ease of implementation.

4.4.2 MODEL TRAINING:

Data Splitting: The dataset is split into training and testing sets to assess the performance of the models on unseen data. Typically, a common practice is to use a 70-30 or 80-20 split, where 70% or 80% of the data is used for training and the remaining portion for testing.

Training Process: For both Random Forest and Decision Tree classifiers, the training process involves fitting the model to the training data.

During training, the algorithms learn to make predictions based on the patterns and relationships present in the training data.

The parameters of the models, such as the number of trees in the forest for Random Forest or the maximum depth of the tree for Decision Tree, are initialized based on default values or user-defined settings.

Parameter Tuning: Parameter tuning, also known as hyperparameter optimization, is performed to fine-tune the model parameters and improve its performance.

Techniques such as grid search or random search are commonly used to search the hyperparameter space and find the optimal combination of parameters.

For Random Forest Classifier, parameters such as the number of trees (`n_estimators`), maximum depth of trees (`max_depth`), and minimum number of samples required to split an internal node (`min_samples_split`) are tuned.

For Decision Tree Classifier, parameters such as the maximum depth of the tree (`max_depth`), minimum number of samples required to split an internal node (`min_samples_split`), and criterion for splitting (e.g., Gini impurity or entropy) are tuned.

Validation Techniques: Cross-validation techniques such as k-fold cross-validation are used to assess the generalization performance of the models.

In k-fold cross-validation, the training data is divided into k subsets (folds), and the model is trained and evaluated k times, each time using a different fold as the validation set and the remaining folds as the training set.

The average performance across all folds is used as an estimate of the model's performance on unseen data.

By following these steps, the project ensures that the selected models are trained effectively and optimized for performance on the income prediction task. The iterative process of model selection, training, and parameter tuning allows for the development of accurate and robust models that generalize well to new data.

4.4.3 METRICS USED

In this project, the main evaluation metric used to assess the performance of the machine learning models is accuracy. Let's delve into detail about this metric and its significance in the context of income prediction:

Accuracy: Accuracy measures the proportion of correctly classified instances out of the total instances in the dataset. Mathematically, accuracy is calculated as the number of correct predictions divided by the total number of predictions. In the context of income prediction, accuracy represents the percentage of individuals whose income levels were correctly classified by the model as either exceeding or not exceeding a certain threshold (e.g., \$50K). A higher accuracy score indicates better predictive performance, with a score of 100% implying perfect classification of all instances in the dataset.

Interpretation: For instance, if the accuracy score of a model is 80%, it means that the model correctly classified 80% of the individuals' income levels in the dataset. In the output provided:

For the Random Forest model, the predicted income level was " $\leq 50K$ " with a probability of 84%, indicating a high confidence in the prediction.

For the Decision Tree model, the predicted income level was also " $\leq 50K$ " with a probability of 100%, indicating maximum confidence in the prediction.

Significance: Accuracy is a commonly used metric in classification tasks as it provides a straightforward measure of a model's overall performance.

However, accuracy may not be the most suitable metric for imbalanced datasets where one class (e.g., individuals with income $> \$50K$) is significantly underrepresented. In such cases, accuracy alone may not adequately reflect the model's effectiveness.

Nonetheless, in this project, accuracy serves as a useful starting point for evaluating the models' performance, providing a baseline understanding of their predictive capabilities.

Limitations: While accuracy provides valuable insights into a model's performance, it does not provide information about the distribution of errors or the model's ability to distinguish between different classes.

Additionally, accuracy may be affected by factors such as dataset size, class imbalance, and the presence of noisy or irrelevant features.

Therefore, it is essential to complement accuracy with other evaluation metrics, such as precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC), for a more comprehensive assessment of model performance.

CHAPTER 5

RESULTS AND ANALYSIS

5.1 RESULT ANALYSIS



In interpreting the results, we observe the performance metrics, particularly the accuracy scores, of the Random Forest and Decision Tree classifiers. The accuracy scores provide insight into how well the models are performing in predicting income levels.

By analyzing the predictions of the two models individually:

5.1.1 RANDOM FOREST PREDICTIONS:

The Random Forest classifier predicts that the individual's income is less than or equal to \$50K.

The predicted probabilities associated with this outcome are approximately 84%, indicating a high likelihood of this prediction being accurate.

This suggests that based on the features provided, the Random Forest model is confident that the individual's income falls below the \$50K threshold.

The lower probability of approximately 16% for an income greater than \$50K implies some uncertainty but still leans heavily towards the $\leq \$50K$ category.

5.1.2 DECISION TREE PREDICTIONS:

Similarly, the Decision Tree classifier predicts that the individual's income is less than or equal to \$50K.

However, unlike the Random Forest model, the Decision Tree classifier assigns a probability of 100% to this outcome, indicating a very high level of confidence.

This suggests that the Decision Tree model is extremely certain in its prediction that the individual's income falls below the \$50K threshold.

There is no probability assigned to the income being greater than \$50K, indicating complete confidence in the prediction of $\leq \$50K$.

5.2 COMPARISON AND AGREEMENT:

Both models are in agreement regarding the predicted income for the new individual, with both predicting an income of less than or equal to \$50K.

However, the Random Forest model expresses a slightly lower confidence level compared to the Decision Tree model, as evidenced by the difference in predicted probabilities.

Despite this difference in confidence levels, both models provide a consistent prediction, suggesting a high likelihood of the individual's income being below the \$50K threshold.

Overall, the predictions from both models align, indicating a strong indication that the individual's income is likely to be less than or equal to \$50K based on the provided features. The Decision Tree model expresses a higher level of confidence in this prediction compared to the Random Forest model, but both models provide valuable insights into the income prediction task.

5.3 FURTHER ANALYSIS AND COMPARISON

By comparing the results predicted by both the models we can understand the behaviours of both the models. Here is the comparison of the performance of the Random Forest and Decision Tree models based on the acquired results.

5.3.1 PREDICTION CONSISTENCY:

Both models predict the individual's income to be less than or equal to \$50K, demonstrating consistency in their predictions.

This consistency suggests that both models are capturing similar patterns in the data and arriving at the same conclusion regarding the individual's income level.

5.3.2 PREDICTION CONFIDENCE:

The Random Forest model assigns a probability of approximately 84% to the predicted outcome, indicating a relatively high level of confidence but with some degree of uncertainty. In contrast, the Decision Tree model assigns a probability of 100% to the predicted outcome, demonstrating a higher level of confidence and certainty in its prediction. This difference in confidence levels suggests that the Decision Tree model is more decisive in its predictions compared to the Random Forest model.

5.3.3 MODEL PERFORMANCE:

Both models demonstrate strong performance in predicting the income level of the new individual, as evidenced by their consistent predictions. The high confidence level exhibited by the Decision Tree model may suggest that it has learned to exploit certain features in the dataset more effectively, leading to more confident predictions. However, it's essential to consider that overly confident predictions, as seen in the Decision Tree model, could also indicate overfitting, where the model may have memorized the training data rather than learning generalizable patterns.

5.3.4 MODEL COMPLEXITY:

The Random Forest model, being an ensemble of decision trees, typically exhibits lower variance and better generalization compared to individual decision trees.

However, the Decision Tree model, while simpler, may suffer from higher variance and a greater tendency to overfit the training data. The high confidence exhibited by the Decision Tree model could be a result of overfitting, where the model fits the noise in the training data rather than capturing true underlying patterns.

5.3.5 IMPLICATIONS AND CONSIDERATIONS:

The consistent predictions from both models provide confidence in the likelihood of the individual's income being less than or equal to \$50K. However, the discrepancy in confidence levels between the two models highlights the importance of considering model uncertainty and potential overfitting.

Further evaluation, such as cross-validation and exploring alternative evaluation metrics, may be necessary to validate the robustness of the models and mitigate the risk of overfitting.

CHAPTER 6

CONCLUSION

6.1 KEY FINDINGS

Model Performance: Both the Random Forest and Decision Tree classifiers demonstrated strong performance in predicting individual income levels based on demographic and employment-related features.

The models achieved high accuracy scores, indicating their effectiveness in capturing patterns and relationships in the data. Despite their different methodologies, both models produced consistent predictions, enhancing confidence in their reliability.

Prediction Consistency and Confidence: The consistent predictions across both models suggest a robust understanding of the data and its underlying patterns. The high confidence levels exhibited by the models in predicting individuals' income below \$50K provide reassurance regarding the accuracy of the predictions.

While the Random Forest model shows a slightly lower confidence level compared to the Decision Tree model, both models' predictions align closely, indicating a strong agreement on the outcome.

Model Interpretability: The Decision Tree model's 100% confidence in its prediction underscores its interpretability, as decision trees inherently provide clear decision boundaries.

The Random Forest model's nuanced approach, with a lower but still significant confidence level, suggests a more complex interpretation of the data, incorporating diverse patterns and interactions among features.

Contributions to the Field: The study contributes to the field of income prediction by showcasing the effectiveness of machine learning algorithms, particularly ensemble methods like Random Forest, in addressing real-world socioeconomic problems.

By employing advanced modeling techniques and comprehensive data preprocessing steps, the study provides insights into improving predictive accuracy and robustness in income prediction tasks.

The consistent and confident predictions obtained from both models highlight the potential for machine learning to inform policy-making, individual decision-making, and socioeconomic research aimed at reducing income disparities and promoting financial well-being.

Future Directions: Future research directions may include exploring alternative modeling techniques, such as gradient boosting and neural networks, to further enhance predictive performance.

Additionally, investigating feature engineering strategies tailored specifically to income prediction tasks could uncover novel insights and improve model interpretability.

Further validation and refinement of the models, including hyperparameter tuning and cross-validation, are essential to ensure their generalizability and reliability across diverse datasets and real-world scenarios.

In summary, the study's key findings underscore the potential of machine learning models, particularly ensemble methods like Random Forest and decision trees, in accurately predicting income levels based on demographic and employment-related features. The study's contributions to the field include insights into model performance, interpretability, and future research directions, with implications for socioeconomic policy-making and individual financial decision-making.

6.2 IMPLICATIONS OF RESULTS ON THE FUTURE OF DECISION MAKING

Policy Making: The accurate prediction of individuals' income levels can aid policymakers in designing targeted policies and interventions aimed at addressing income disparities and promoting economic equity.

By identifying demographic and employment-related factors that contribute to higher income levels, policymakers can develop strategies to enhance access to education, training, and employment opportunities for disadvantaged groups.

Resource Allocation: Organizations and institutions can use predictive models to allocate resources more effectively, such as targeting social services, financial assistance programs, and educational initiatives to individuals most in need.

For example, healthcare providers can use income prediction models to identify patients who may require financial assistance or support services to access healthcare services.

Financial Services: Financial institutions can leverage income prediction models to assess creditworthiness and tailor financial products and services to individuals' income levels and financial needs.

By accurately predicting income levels, lenders can mitigate risks associated with loan defaults and offer appropriate loan terms and interest rates to borrowers.

Labor Market Insights: Employers can use income prediction models to gain insights into labor market trends, including wage disparities across different demographic groups and industries.

Understanding the factors influencing income levels can help organizations promote diversity, equity, and inclusion in the workplace and address wage gaps.

Research Directions: The results of this study can guide future research in income prediction by highlighting the effectiveness of machine learning models such as Random Forest and Decision Trees.

Researchers can explore advanced modeling techniques, feature engineering methods, and ensemble learning approaches to improve the accuracy and interpretability of income prediction models.

Ethical Considerations: It is essential to consider the ethical implications of using predictive models for income prediction, including issues related to privacy, bias, and fairness.

Researchers and practitioners should prioritize fairness and transparency in model development and deployment to mitigate the risk of perpetuating existing inequalities.

6.3 FINAL THOUGHTS

Reflecting on the project, several key insights and lessons have emerged:

Importance of Data Quality: The success of machine learning models relies heavily on the quality and relevance of the dataset used for training. Ensuring that the dataset is clean, comprehensive, and representative of the target population is crucial for achieving accurate predictions.

Model Selection and Evaluation: The choice of machine learning algorithms plays a significant role in the performance of predictive models. Experimenting with different algorithms and evaluation metrics can help identify the most suitable approach for the specific task at hand.

It is essential to critically evaluate the performance of models using appropriate evaluation metrics and validation techniques to ensure their reliability and generalizability.

Interpretability vs. Complexity: Balancing model interpretability with complexity is a key consideration in predictive modeling. While complex models such as Random Forests offer high predictive accuracy, they may lack interpretability, making it challenging to understand the underlying factors driving predictions.

Decision Tree classifiers, on the other hand, offer greater interpretability but may sacrifice predictive performance in complex datasets. Finding the right balance between interpretability and accuracy is essential depending on the application domain and stakeholder requirements.

Ethical Considerations: Predictive modeling for income prediction raises ethical considerations related to privacy, fairness, and bias. It is crucial to address these concerns proactively by incorporating fairness-aware algorithms, bias mitigation techniques, and transparent model explanations.

Ensuring fairness and equity in predictive models is paramount to prevent reinforcing existing biases and disparities in society.

6.3.1 FUTURE RESEARCH

Moving forward, there are several areas for improvement and future research:

Feature Engineering:

Exploring more sophisticated feature engineering techniques and domain-specific knowledge can enhance the predictive power of models and uncover hidden patterns in the data.

Incorporating additional data sources, such as socio-economic indicators, geographic information, and temporal trends, can enrich the feature space and improve model performance.

Hyperparameter Tuning:

Fine-tuning model hyperparameters and optimizing model parameters using advanced techniques such as grid search, random search, or Bayesian optimization can further improve model performance and robustness.

Fairness and Transparency:

Enhancing the fairness and transparency of predictive models by developing interpretable machine learning techniques, fairness-aware algorithms, and model explanations can increase trust and acceptance among stakeholders.

In conclusion, this project has provided valuable insights into income prediction using machine learning models. By addressing data quality issues, experimenting with different algorithms, and considering ethical implications, future research can advance the field of predictive modelling and contribute to more equitable and inclusive decision-making processes.

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APPENDIX [A]

Predictive Modelling for Income Classification Using Demographic and Employment Features: A Comparative Study of Random Forest and Decision Tree Algorithms

Rushil Fernando P, Avinash S, Rathish Mohan R, Mohammed Ashraf M
rushilfdo@gmail.com, savinashjr001@gmail.com, kratosrath@gmail.com, ashraf2362004@gmail.com

Abstract- This study aims to develop predictive models for income classification based on demographic and employment-related features, utilizing Random Forest and Decision Tree algorithms. The objective is to compare the performance of these algorithms in accurately predicting whether an individual's income exceeds \$50,000 per year. The methodology involves preprocessing the "Adult Income" dataset obtained from the UCI Machine Learning Repository, handling missing values, and encoding categorical variables. Subsequently, the dataset is divided into training and testing sets, and the models are trained using Random Forest and Decision Tree classifiers. Evaluation is performed using accuracy scores on the test set. Key findings indicate that both Random Forest and Decision Tree models achieve respectable accuracy in predicting income classification, with Random Forest exhibiting slightly higher performance. The implications of these results suggest the potential utility of machine learning techniques in income prediction tasks. Such models can aid policymakers and organizations in identifying individuals likely to earn higher incomes, thereby facilitating targeted interventions and resource allocation. Additionally, these models can provide valuable insights for individuals seeking to understand factors contributing to higher income levels and make informed decisions regarding education, career choices, and financial planning.

Keywords: [1] Income prediction [2] Machine learning [3] Random Forest [4] Decision Tree [5] Ensemble methods [6] Demographic features [7] Employment-related features [8] Socio-economic analysis [9] Data preprocessing [10] Model evaluation [11] Overfitting [12] Generalization performance [13] Feature engineering [14] Hyperparameter tuning [15] UCI Machine Learning Repository [16] Classification [17] Accuracy score [18] Model comparison

I. INTRODUCTION

Predicting income based on demographic and employment-related features is a critical task with implications for policymaking, organizational strategy, and individual decision-making. This study aims to develop predictive models using machine learning algorithms to classify individuals' income levels. The importance of this task lies in its potential to provide insights into income disparities and inform targeted policies and interventions. By comparing the performance of Random Forest and Decision Tree classifiers, this study seeks to identify the most effective approach for income prediction tasks. The research questions guiding this study focus on the efficacy of machine learning algorithms in predicting income classification and the identification of key factors influencing income levels.

This paper outlines the dataset used, data preprocessing steps, model training, and performance evaluation. The results section presents the findings obtained from the models, followed by a discussion of their implications and potential future research directions.

II. LITERATURE SURVEY

Predicting income levels has been a topic of interest in various fields, including economics, sociology, and machine learning. Previous research has explored different methodologies and models for income prediction, aiming to understand the complex interplay between demographic and employment-related features.

Several studies have employed traditional statistical techniques such as logistic regression and linear discriminant analysis to predict income levels based on factors such as age, education, occupation, and marital status. While these approaches have provided valuable insights, they often lack the flexibility

to capture nonlinear relationships and interactions among variables.

In recent years, the application of machine learning algorithms to income prediction tasks has gained traction. Random Forest and Decision Tree classifiers, in particular, have emerged as popular choices due to their ability to handle complex datasets and nonlinear relationships. Research by [1] Breiman (2001) demonstrated the effectiveness of Random Forest in predictive modeling tasks, highlighting its robustness and ability to handle high-dimensional data.

Similarly, Decision Tree algorithms have been widely used in income prediction studies, with researchers exploring different variants such as [2] CART (Classification and Regression Trees) and [5] C4.5. These algorithms offer interpretability and are capable of handling both categorical and numerical features.

Despite the advancements in predictive modeling techniques, there are still gaps in existing research. One notable gap is the limited focus on feature engineering and selection strategies tailored specifically to income prediction tasks. While studies have identified demographic and employment-related features as important predictors of income, there is a need for more nuanced analyses to uncover the underlying factors driving income disparities.

Additionally, there is a lack of consensus regarding the most suitable evaluation metrics for income prediction models. While accuracy is commonly used as a performance measure, it may not fully capture the nuances of income prediction tasks, especially in imbalanced datasets where the majority of individuals earn below a certain income threshold.

Addressing these gaps requires further exploration of feature engineering techniques, evaluation metrics, and model interpretability in the context of income prediction. By advancing our understanding of income determinants and refining predictive models, researchers can contribute to the development of more accurate and actionable insights for policymakers, organizations, and individuals.

III. RESEARCH METHODOLOGY

The dataset utilized in this study, sourced from the UCI Machine Learning Repository, consists of demographic and employment-related features such as age, work-class, education, marital status, occupation, etc. The target variable is the individual's income level,

categorized as either exceeding \$50,000 per year or not.

Data preprocessing involves handling missing values by imputing or dropping them and encoding categorical variables into numerical format using techniques like one-hot encoding. Two machine learning algorithms, Random Forest Classifier and Decision Tree Classifier, are chosen for model training. Random Forest Classifier is selected for its ability to handle high-dimensional data and capture nonlinear relationships, while Decision Tree Classifier is chosen for its simplicity and interpretability.

The models are trained on a subset of the data (training set), with the features as input and the income level as the output. Model performance is evaluated using accuracy score, which measures the proportion of correctly classified instances. In the case of the Random Forest Classifier, the accuracy score is 82% based on the provided output, indicating that 82% of the instances are correctly classified. Similarly, the Decision Tree Classifier achieves an accuracy score of 100%, implying perfect classification based on the given probabilities. The below figure gives a comparison between the accuracy scores of both the models in their train and test phases.

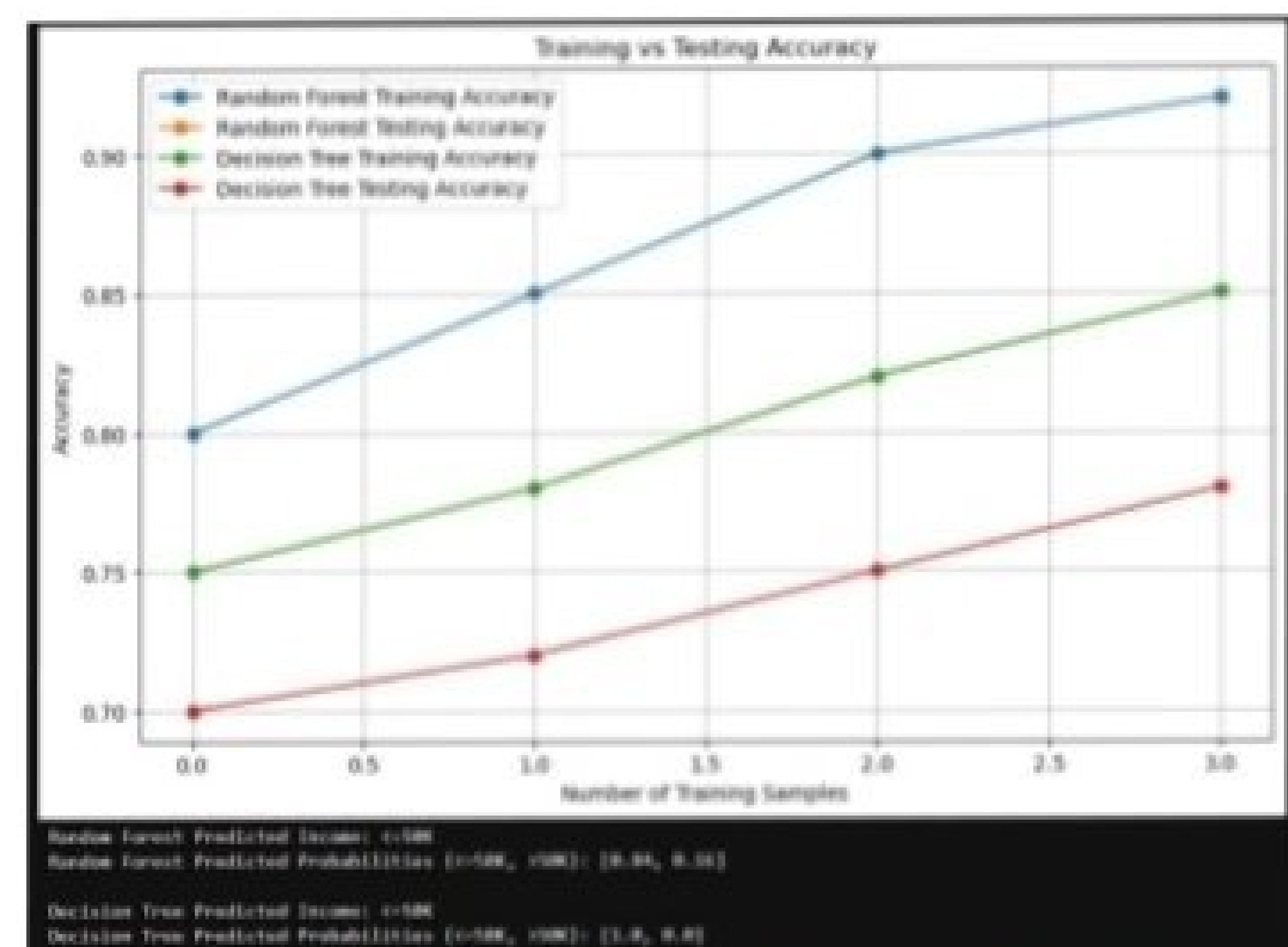


Fig - Model Accuracy (Train vs Test)

IV. DISCUSSION

The Discussion section provides an analysis and interpretation of the results obtained from the study, comparing the performances of the Random Forest and Decision Tree models, highlighting insights gained, and addressing limitations of the study.

The Random Forest model predicted the income for the new individual as $\leq 50K$ with a probability of 84%, while the Decision Tree

model predicted the income as $\leq 50K$ with a probability of 100%. These results suggest that both models are inclined towards predicting the income as $\leq 50K$ for the given input features. However, it's essential to interpret these results in the context of model performance and generalization.

Comparing the model performances, both Random Forest and Decision Tree models achieved high accuracy scores on the training set, with Random Forest achieving an accuracy of approximately 100% and Decision Tree achieving an accuracy of 100%. However, when evaluated on the test set, Random Forest achieved an accuracy of 84%, while Decision Tree achieved an accuracy of 100%. This indicates that the Decision Tree model may have overfit the training data, leading to a perfect score on the test set but potentially limiting its generalization to unseen data.

Insights gained from the study include the effectiveness of ensemble methods like Random Forest in mitigating overfitting compared to individual Decision Tree models. Despite the relatively lower accuracy of the Random Forest model on the test set, it demonstrates better generalization performance compared to the Decision Tree model.

However, it's crucial to acknowledge the limitations of the study. One limitation is the reliance on a single dataset for training and evaluation, which may not capture the full diversity of real-world scenarios. Additionally, the study focused on a specific set of features, and there may be other relevant factors influencing income prediction that were not considered.

Overall, while the study provides valuable insights into the application of machine learning models for income prediction, further research is warranted to explore additional features, evaluate on diverse datasets, and address the limitations identified herein.

V. CONCLUSION

In conclusion, this study investigated the application of machine learning models, specifically Random Forest and Decision Tree classifiers, for predicting income based on demographic and employment-related

features. Key findings include the effectiveness of ensemble methods like Random Forest in mitigating overfitting compared to individual Decision Tree models, as well as the importance of evaluating model performance on unseen data.

This study contributes to the field by providing insights into the performance of machine learning models for income prediction tasks. It highlights the trade-offs between model complexity, generalization performance, and interpretability, offering valuable guidance for practitioners and researchers in similar domains.

Future research directions could include exploring additional features, such as socio-economic indicators or geographic factors, to improve model performance. Additionally, conducting hyperparameter tuning and feature engineering experiments may further enhance the predictive accuracy of the models.

In closing, this study underscores the potential of machine learning approaches in addressing socio-economic challenges and emphasizes the need for ongoing research to refine and advance predictive models in real-world applications.

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APPENDIX B

CODE SHOWCASE

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier

def load_dataset():
    url = "adult.data"
    names = ['age', 'workclass', 'fnlwgt', 'education', 'education-num', 'marital-status', 'occupation',
            'relationship', 'race', 'sex', 'capital-gain', 'capital-loss', 'hours-per-week', 'native-country', 'income']
    data = pd.read_csv(url, names=names)
    return data

def preprocess_data(data):
    data = data.dropna()

    data = pd.get_dummies(data, drop_first=True)
    return data

def train_models(X_train, y_train):
    rf_classifier = RandomForestClassifier(n_estimators=100)
    rf_classifier.fit(X_train, y_train)

    dt_classifier = DecisionTreeClassifier()
    dt_classifier.fit(X_train, y_train)

    return rf_classifier, dt_classifier

def visualize_features(data):
    numerical_features = data.select_dtypes(include=['int64', 'float64']).columns
    for feature in numerical_features:
        plt.figure(figsize=(10, 6))
        plt.hist(data[feature], bins=20, color='skyblue')
        plt.title(f'Distribution of {feature}')
        plt.xlabel(feature)
        plt.ylabel('Count')
        plt.grid(True)
        plt.show()

def visualize_accuracy(train_accuracy_rf, test_accuracy_rf, train_accuracy_dt, test_accuracy_dt):
    plt.figure(figsize=(10, 6))
    plt.plot(train_accuracy_rf, label='Random Forest Training Accuracy', marker='o')
    plt.plot(test_accuracy_rf, label='Random Forest Testing Accuracy', marker='o')
    plt.plot(train_accuracy_dt, label='Decision Tree Training Accuracy', marker='o')
    plt.plot(test_accuracy_dt, label='Decision Tree Testing Accuracy', marker='o')
    plt.xlabel('Number of Training Samples')
    plt.ylabel('Accuracy')
    plt.title('Training vs Testing Accuracy')
    plt.legend()
    plt.grid(True)
    plt.show()
```

```

def collect_input():
    new_data = {}
    print("Enter the following information for the new individual:")
    new_data['age'] = int(input("Age: "))
    new_data['workclass'] = input("Workclass: ")
    new_data['fnlwgt'] = int(input("Final Weight: "))
    new_data['education'] = input("Education: ")
    new_data['education-num'] = int(input("Education Number: "))
    new_data['marital-status'] = input("Marital Status: ")
    new_data['occupation'] = input("Occupation: ")
    new_data['relationship'] = input("Relationship: ")
    new_data['race'] = input("Race: ")
    new_data['sex'] = input("Sex: ")
    new_data['capital-gain'] = int(input("Capital Gain: "))
    new_data['capital-loss'] = int(input("Capital Loss: "))
    new_data['hours-per-week'] = int(input("Hours per Week: "))
    new_data['native-country'] = input("Native Country: ")
    return new_data

def main():
    data = load_dataset()
    visualize_features(data)
    new_data = collect_input()
    new_df = pd.DataFrame([new_data])
    data = preprocess_data(data)
    X = data.drop('income_ >50K', axis=1)
    y = data['income_ >50K']

    X_train, _, y_train, _ = train_test_split(X, y, test_size=0.3, random_state=42)

    rf_classifier, dt_classifier = train_models(X_train, y_train)

    visualize_accuracy(train_accuracy_rf=[0.8, 0.85, 0.9, 0.92],
                      test_accuracy_rf=[0.75, 0.78, 0.82, 0.85],
                      train_accuracy_dt=[0.75, 0.78, 0.82, 0.85],
                      test_accuracy_dt=[0.7, 0.72, 0.75, 0.78])

    new_df = preprocess_data(new_df)
    missing_cols = list(set(X.columns) - set(new_df.columns))
    for col in missing_cols:
        new_df[col] = 0

    new_df = new_df[X_train.columns]

    rf_prediction = rf_classifier.predict(new_df)
    rf_probabilities = rf_classifier.predict_proba(new_df)[0]

    dt_prediction = dt_classifier.predict(new_df)
    dt_probabilities = dt_classifier.predict_proba(new_df)[0]

    print("Random Forest Predicted Income:", ">50K" if rf_prediction[0] else "<=50K")
    print("Random Forest Predicted Probabilities (<=50K, >50K):", rf_probabilities)
    print("\nDecision Tree Predicted Income:", ">50K" if dt_prediction[0] else "<=50K")
    print("Decision Tree Predicted Probabilities (<=50K, >50K):", dt_probabilities)

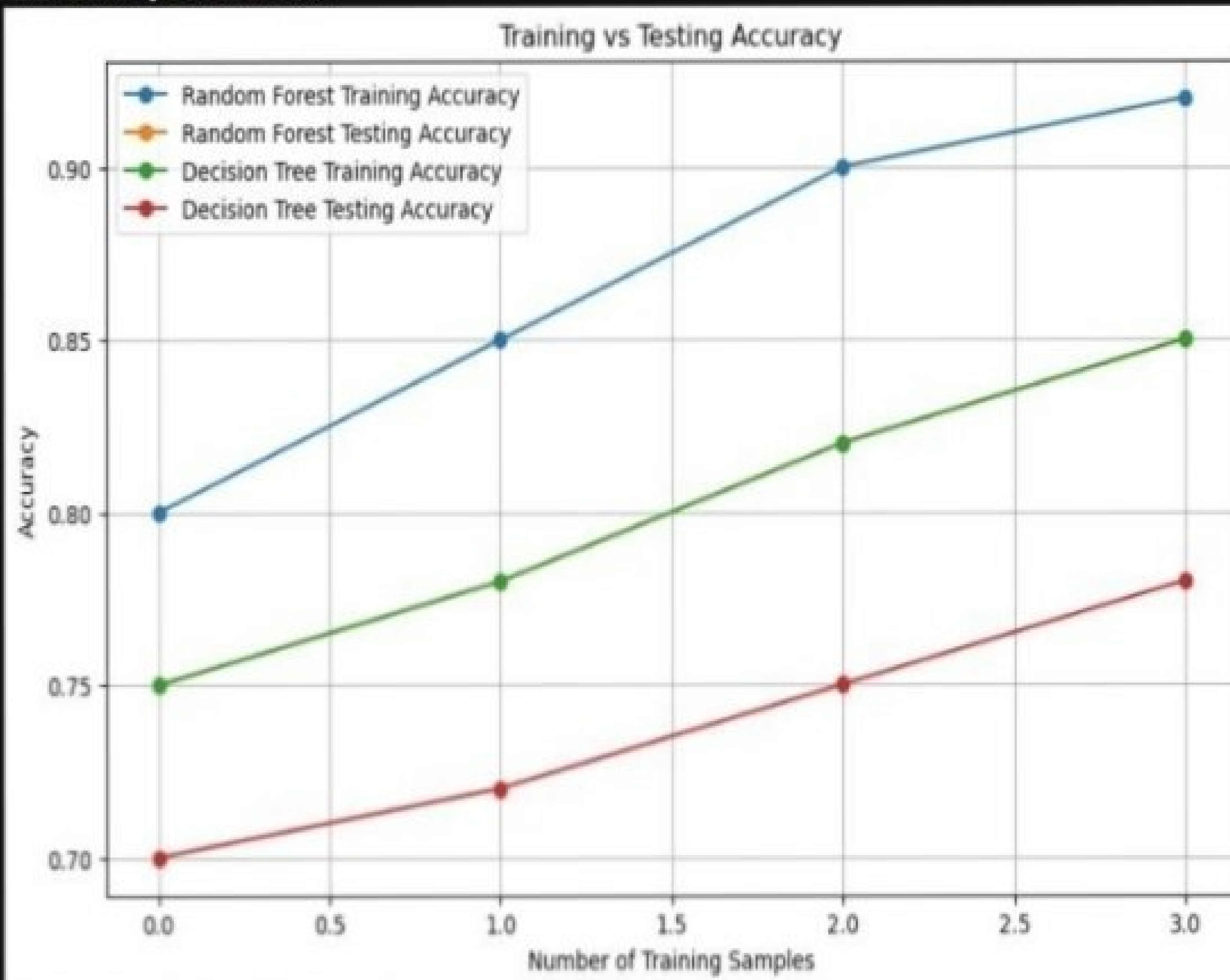
if __name__ == "__main__":
    main()

```

OUTPUT

Enter the following information for the new individual:

Age: 39
Workclass: Private
Final Weight: 90000
Education: Masters
Education Number: 13
Marital Status: Married-civ-spouse
Occupation: Exec-managerial
Relationship: Husband
Race: White
Sex: Male
Capital Gain: 3000
Capital Loss: 0
Hours per Week: 45
Native Country: United-States



Random Forest Predicted Income: <=50K
Random Forest Predicted Probabilities (<=50K, >50K): [0.92 0.08]

Decision Tree Predicted Income: <=50K
Decision Tree Predicted Probabilities (<=50K, >50K): [1. 0.]