ADULT INCOME PREDICTION USING MACHINE LEARNING

Dissertation submitted in fulfilment of the requirements for the Degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

By

DASA SRINIVAS

JYOSHIKA RAYANA

YASHWANTH BOORAM

Registration numbers:12216692,12216304,12224006

Faculty

ENJULA UCHOI (29634)

School of Computer Science and Engineering

Lovely Professional University

Phagwara, Punjab (India)

Month…… Year ……

DECLARATION STATEMENT

We hereby declare that the research work reported in the dissertation/dissertation proposal entitled "ADULT INCOME PREDICTION USING MACHINE LEARNING" in partial fulfilment of the requirement for the award of Degree for Bachelor of Technology in Computer Science and Engineering at Lovely Professional University, Phagwara, Punjab is an authentic work carried out under supervision of our research supervisor Mr. ENJULA UCHOI. We have not submitted this work elsewhere for any degree or diploma.

We understand that the work presented herewith is in direct compliance with Lovely Professional University's Policy on plagiarism, intellectual property rights, and highest standards of moral and ethical conduct. Therefore, to the best of our knowledge, the content of this dissertation represents authentic and honest research effort conducted, in its entirety, by me. We are fully responsible for the contents of our dissertation work.

Signature of Candidate's,

Dasa Srinivas
Jyoshika Rayana
Yashwanth Booram
R.No's:13,14,68

SUPERVISOR'S CERTIFICATE

This is to certify that the work reported in the B.Tech Dissertation/dissertationproposal entitled **" ADULT INCOME PREDICTION USING MACHINE LEARNING"**, submitted by **Yashwanth Booram** at **Lovely Professional University, Phagwara, India** is a bonafide record of his / her original work carried out under my supervision. This work has not been submitted elsewhere for any other degree.

Signature of Supervisor

Date:

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ABSTRACT

One of the most important tasks in socioeconomic studies and policy-making is estimating the income levels of individuals. Using the Adult Income dataset, this research study proposes a machine learning method to estimate adult income by utilizing features, random forest classifier models, and data preprocessing.

The methodology includes preprocessing processes for the data, such as employing median and most frequent strategies to impute missing values for numerical and categorical categories, respectively. To transform categorical variables into a numerical format for model training, one-hot encoding is used. Because of its capacity to manage intricate linkages and feature interactions, the Random Forest Classifier is used as the predictive model.

The predictive model chosen is the Random Forest Classifier, which is renowned for its capacity to manage intricate linkages and feature interactions. The preprocessed dataset is used to train the model, which makes accurate income.

Important measures including accuracy, mean absolute error (MAE), and confusion matrix are computed to assess the model's performance. With a thorough study of model performance and insights into feature relevance, the results show how effective the suggested strategy is at properly predicting income levels.

Moreover, an example forecast for an individual's income level illustrates how the model might be used in practice. This demonstrates the model's usefulness in the real world and its capacity to support decision-makers across a range of industries, including the social sciences, public policy, and finance.

By offering a trustworthy and understandable approach for predicting income, this study makes a substantial contribution to the field of socioeconomic analysis. The created model is a useful tool for tackling income disparity and creating focused interventions, in addition to improving our understanding of income dynamics.

Keywords: Machine Learning, Income Prediction, Random Forest Classifier, Data Preprocessing, Feature Engineering, Socioeconomic Analysis, Missing Data Imputation, Model Evaluation, Decision Support System.

INTRODUCTION

Within the field of socioeconomic research and policy development, income level prediction is essential for comprehending economic dynamics, tackling inequality, and creating focused responses. Policymakers, economists, and social scientists need accurate income prediction models in order to evaluate economic well-being, identify trends, and make well-informed decisions.
One popular dataset for machine learning research is Adult Income, which offers a wealth of data on people's socioeconomic and demographic characteristics. With a particular focus on tools like Pandas and Scikit-Learn, this research uses this dataset to construct a strong income prediction model utilizing cutting-edge machine learning techniques.
The methodology consists of multiple important processes, the first of which is data preprocessing using methods like one-hot encoding of categorical variables and imputation of missing values. These procedures assure data quality and get the dataset ready for training the model. Advanced machine learning algorithms including Random Forest Classifier, Decision Trees, and Logistic Regression are also included in the study, demonstrating the applicability and effectiveness of these methods for income prediction tasks.

Key project components and steps:

1. Using the Adult Income dataset, create a precise and trustworthy income prediction model. For effective data processing and model training, combine Pandas with Scikit-Learn.
2. Analyze the model's performance using metrics that demonstrate the efficacy of the selected machine learning techniques, such as confusion matrix, mean absolute error (MAE), and accuracy.
3. Highlight the usefulness and applicability of the generated model in the actual world by using it to anticipate people's income levels based on their demographic and socioeconomic characteristics.

The results of this study should greatly advance the field of socioeconomic analysis by offering a solid framework for predicting income. In fields including public policy, finance, and the social sciences, this study seeks to enable evidence-based policymaking and provide decision-makers with useful insights through the use of sophisticated machine learning algorithms and data-driven methodologies.

LITERATURE REVIEW

Numerous academic disciplines, including economics, finance, and machine learning, have conducted substantial research on the use of machine learning algorithms for income prediction. The literature review highlights the development of income prediction systems and their real-world applications while offering insights into the approaches, conclusions, and research gaps.

1. **The Logistic Regression Model:**
   - Logistic regression was used by Hossain et al. (2018) to forecast income levels depending on socioeconomic and demographic variables. Their research showed that Logistic Regression models are easily interpreted and straightforward, which makes them appropriate for use in financial institution decision-making and policy formation.

   - In order to estimate income through credit risk assessment,used logistic regression, demonstrating the usefulness of this technique in assessing borrowers' creditworthiness and establishing loan eligibility.

2. **Decision Trees:**
   - Using Gao et al. (2019) Decision Trees were utilized to forecast income groups based on attributes like marital status, occupation, and education level. Their research demonstrated how well the algorithm handled categorical data and captured non-linear correlations, offering insightful information for resource allocation and targeted marketing.

   - By adding ensemble approaches like Random Forest, Li expanded on this research and improved forecast resilience and accuracy. The significance of ensemble approaches in enhancing model performance and generalization was underscored by their work.

3. **Random Forest:**
   - Wu et al. (2017) demonstrated the efficacy of Random Forest in detecting income-related trends and customizing marketing strategies by using it for income prediction in customer segmentation. Their investigation proved the algorithm's capacity to manage high-dimensional data and generate accurate forecasts in practical contexts.

- Gao et al. (2019) used to forecast income levels in healthcare settings, which helped with resource allocation and patient risk assessment. Their analysis demonstrated how adaptable and scalable the algorithm is at managing a range of datasets and challenging prediction tasks.

4. Gaps and Future Directions:

- There are still a number of holes in the research field despite the progress in income prediction systems. Integrating external aspects into prediction models, such as socio-cultural influences, area demography, and economic policies, is one of the issues. Subsequent investigations may concentrate on integrating these elements to improve forecast precision and applicability in other scenarios.

- An additional void exists in the assessment of interpretability and fairness of models, particularly when it comes to ethical decision-making processes. To tackle these issues, research endeavors ought to focus on creating fair and transparent models for predicting income that conform to moral principles and societal norms.

Pandas and Scikit-Learn: The project leverages popular Python libraries, such as Pandas and Scikit-Learn, which facilitate data manipulation, preprocessing, and model building. These tools are widely used in data science and machine learning projects.

Real-World Application: The created income prediction model can be used in a variety of industries. It can help governments create targeted welfare programs, help businesses structure salaries fairly, help financial institutions determine who is eligible for loans, and allow market researchers to customize marketing campaigns depending on income demographics. This practical application highlights the model's worth in supporting data-driven decision-making and successfully tackling socioeconomic issues.

There are several machine learning algorithms commonly used for training a Income Prediction model using Python. Here are some of the most popular algorithms:

Logistic Regression: This algorithm is often used for binary classification problems like Income prediction. It models the probability of an individual having Income based on input features.

Decision Trees: Decision trees are useful in many different fields since they provide intuitive insights for predicting income. Retail companies, for instance, can divide their clientele depending on income levels and customize marketing campaigns by using Decision Trees. Decision trees can also be used by government organizations to pinpoint demographic groups that are susceptible to low income and create interventions aimed at improving socioeconomic conditions.

Random Forest: With a wide range of practical applications in income prediction, Random Forest models are renowned for their resilience and capacity to manage intricate interactions. These models can be used by real estate agents to forecast property values based on the income distribution of the neighborhood, which can help with investment and property valuation decisions.

K-Nearest Neighbors (K-NN): K-NN classifies individuals based on the majority class of their k-nearest neighbors in feature space. It is adaptable for Income prediction.

Neural Networks: Deep learning techniques, including various types of neural networks such as feedforward or convolutional neural networks, can be used for complex Income prediction tasks when there's a large amount of data available.

Gradient Boosting: Algorithms like Gradient Boosting and XGBoost are often employed to improve the predictive performance by combining the predictions of multiple weak learners.

Ensemble Learning: Ensemble methods, like AdaBoost and Bagging, combine multiple models to achieve better predictive accuracy.

Gaussian Processes: Gaussian processes are used for regression tasks, and they can be adapted to Income prediction to estimate the likelihood of an individual having Income based on their Salary parameters.

Using machine learning for Income Prediction using Python offers several significant benefits:

Early Detection: Machine learning models can identify patterns and relationships within income data that may not be apparent through traditional methods.

Accuracy: Machine learning models can provide highly accurate predictions based on a combination of multiple parameters. This can lead to more precise and risk assessments.

Customization: Machine learning models can be tailored to individual persons data, allowing for personalized risk assessments and future plans. This customization is particularly valuable in management of income.

Data-Driven Insights: Machine learning can extract valuable insights from extensive income datasets. These insights can be used for further research policy development.

Efficiency: Automated prediction systems can process large volumes of income data quickly.

PROBLEM STATEMENT

Robust approaches for accurately and reliably projecting adult income levels are necessary in the current socioeconomic analysis and policy-making landscape. Even with the abundance of large-scale datasets that cover a wide range of demographic, educational, and occupational characteristics, conventional statistical methods frequently fail to capture the complex correlations that are inherent in income dynamics. By utilizing cutting-edge machine learning techniques and focusing on the Adult Income dataset, this research seeks to close this gap by creating a thorough income prediction model. The main issue this study attempts to solve is how difficult it is to estimate adult income because it depends on so many different elements, from personal characteristics like age, marital status, and education level to professional characteristics like work class and occupation. In addition, the dataset can have categorical variables and missing values, which call for cautious handling and transformation to guarantee data completeness and model interpretability.

Problem Statement:

In order to effectively address these difficulties, the research focuses on the following major goals:

Managing Missing Data: To handle missing values without adding bias to the dataset, robust imputation techniques are used, such as the usage of median for numerical features and most common for categorical characteristics.

Feature engineering: Converting categorical variables into a numerical format using methods like one-hot encoding allows machine learning models to evaluate the data quickly and identify relevant trends.

Model Selection and Evaluation: Testing out different machine learning algorithms, with a focus on the Random Forest Classifier in particular because of its capacity to manage intricate feature interactions and linkages. Metrics like accuracy, mean absolute error (MAE), and confusion matrix are used to evaluate each model's performance in order to determine its predictive power and capacity to generalize to data that has not yet been observed.

Practical Application: By forecasting people's income levels based on their socioeconomic and demographic characteristics, the created income prediction model demonstrates its practical utility. This entails developing an application or user interface that is easy to use so that interested parties, decision-makers, economists, and social scientists may enter pertinent information and get precise revenue projections.

This study intends to make a substantial contribution to the field of socioeconomic analysis and policy-making by thoroughly addressing these issues. The created income prediction model might be a useful tool for comprehending income dynamics, figuring out the main factors that contribute to income inequality, and creating focused interventions that advance social justice and economic well-being.

The ultimate objective is to provide decision-makers with useful information gleaned from data-driven approaches, which will support well-informed policy choices and result in a more equal socioeconomic environment

PROBLEM STATEMENT SOLUTIONS

ProblemStatement:

Accurately predicting adult income levels is difficult because of the intricate interactions between occupational, educational, and demographic characteristics. When working with big and diverse datasets like the Adult Income dataset, traditional statistical methods frequently fail to capture the subtleties of income patterns. The goal of this project is to use cutting-edge machine learning techniques to overcome these obstacles and create a trustworthy income forecast model.

Solution:

Data Loading and Exploration: Data is loaded from a CSV file using the Pandas library. The dataset contains information about individuals, with columns representingfeatures and the target variable "Outcome" indicating whether the individual has income The first 5 rows of the dataset are printed to get a glimpse of the data. Basic information about the dataset is obtained, including the number of rows and columns. Statistical measures of the data (e.g., mean, standard deviation) are calculated and displayed. The distribution of the target variable 'Outcome' is examined to understand the class balance.

Data preparation: Sophisticated data preparation methods are the initial stage in our solution. This includes employing techniques such as most frequent imputation for categorical features and median imputation for numerical features to handle missing data. By guaranteeing the completeness and quality of the data, we reduce the possibility of biases and improve the prediction accuracy.

Feature Engineering: We use feature engineering to prepare the data for machine learning algorithms. One-hot encoding is used to convert categorical variables into numerical representation so that the algorithms can process the data efficiently and identify relevant patterns. To fully capture the variety of factors impacting income levels, this stage is essential.

Model Selection and Evaluation: We test out a number of machine learning models, concentrating on the Random Forest Classifier in particular. Because of its capacity to manage intricate linkages and feature interactions, the Random Forest algorithm is a good fit for this task. We measure the predictive power and resilience of each model by analyzing its performance using metrics

like confusion matrix, mean absolute error (MAE), and accuracy.

Use in Practice: The created income prediction model is more than just a research project; it has real-world applications. We design an application or user interface that is easy for policymakers, economists, social scientists, and stakeholders to input pertinent socioeconomic and demographic data. After that, the model produces precise income forecasts, offering insightful information for formulating policies and making decisions.

Our goal in putting this all-inclusive solution into practice is to advance the field of socioeconomic analysis and policy-making. The created income prediction model is a useful tool for comprehending income dynamics, pinpointing important factors that contribute to income disparity, and creating focused interventions that advance social justice and economic well-being.

In the end, we want to provide stakeholders with useful information gleaned from data-driven approaches so they may make more informed decisions and improve the socioeconomic environment.

CODE:

Importing the Dependencies

```
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import confusion_matrix
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

Loading and analyzing data

```
data = pd.read_csv('adult.csv')
```

```
data.head()
```

```
data = pd.read_csv('adult.csv')
```

```
[62] data.head()
```

	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	race	gender	capital-gain	capital-loss	hours-per-week	native-country	income
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	0	40	United-States	<=50K
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	50	United-States	<=50K
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0	40	United-States	>50K
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	0	40	United-States	>50K
4	18	?	103497	Some-college	10	Never-married	?	Own-child	White	Female	0	0	30	United-States	<=50K

```
# Shape of training data (num_rows, num_columns)

# List column names
```

```
[63] # Shape of training data (num_rows, num_columns)
     data.shape
```

```
(48842, 15)
```

```
[64] # List column names
     data.columns
```

```
Index(['age', 'workclass', 'fnlwgt', 'education', 'educational-num',
       'marital-status', 'occupation', 'relationship', 'race', 'gender',
       'capital-gain', 'capital-loss', 'hours-per-week', 'native-country',
       'income'],
      dtype='object')
```

```
# Show statistical characteristics of data
```

```
[65] # Show statistical caracterisctics of data
     data.describe()
```

	age	fnlwgt	educational-num	capital-gain	capital-loss	hours-per-week
count	48842.000000	4.884200e+04	48842.000000	48842.000000	48842.000000	48842.000000
mean	38.643585	1.896641e+05	10.078089	1079.067626	87.502314	40.422382
std	13.710510	1.056040e+05	2.570973	7452.019058	403.004552	12.391444
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.175505e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.781445e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.376420e+05	12.000000	0.000000	0.000000	45.000000
max	90.000000	1.490400e+06	16.000000	99999.000000	4356.000000	99.000000

Data cleaning and preprocessing

```
# Missing Values in the data:
```

```
[66] df = pd.DataFrame(data)

     # Number of missing values in each column of training data
     missing_val = (df == '?').sum()

     # Replace '?' with NaN (Not a Number)
     df.replace('?', np.nan, inplace=True)

     print("Missing values in data :")
     print(missing_val[missing_val > 0])
```

```
Missing values in data :
workclass         2799
occupation        2809
native-country     857
dtype: int64
```

```
# Identifying numerical and categorial columns
```

```
[67] # Identifying numerical columns
     numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns

     # Identifying categorical columns
     categorical_cols = df.select_dtypes(include=['object', 'category']).columns

     print("Numerical Columns:", numerical_cols)
     print("Categorical Columns:", categorical_cols)
```

```
Numerical Columns: Index(['age', 'fnlwgt', 'educational-num', 'capital-gain', 'capital-loss',
       'hours-per-week'],
      dtype='object')
Categorical Columns: Index(['workclass', 'education', 'marital-status', 'occupation',
       'relationship', 'race', 'gender', 'native-country', 'income'],
      dtype='object')
```

```
# Imputer for numerical data

# Impute numerical columns

# Impute categorical columns
```

```
# Imputer for numerical data
num_imputer = SimpleImputer(strategy='median')
# Imputer for categorical data
cat_imputer = SimpleImputer(strategy='most_frequent')

# Impute numerical columns
df[numerical_cols] = num_imputer.fit_transform(df[numerical_cols])

# Impute categorical columns
df[categorical_cols] = cat_imputer.fit_transform(df[categorical_cols])

print(df)
```

```
        age     workclass    fnlwgt     education  educational-num  \
0      25.0       Private  226802.0          11th              7.0
1      38.0       Private   89814.0       HS-grad              9.0
2      28.0     Local-gov  336951.0    Assoc-acdm             12.0
3      44.0       Private  160323.0  Some-college             10.0
4      18.0       Private  103497.0  Some-college             10.0
...     ...           ...       ...           ...              ...
48837  27.0       Private  257302.0    Assoc-acdm             12.0
48838  40.0       Private  154374.0       HS-grad              9.0
48839  58.0       Private  151910.0       HS-grad              9.0
48840  22.0       Private  201490.0       HS-grad              9.0
48841  52.0  Self-emp-inc  287927.0       HS-grad              9.0
```

```
          marital-status         occupation relationship   race  gender  \
0          Never-married  Machine-op-inspct    Own-child  Black    Male
1      Married-civ-spouse    Farming-fishing      Husband  White    Male
2      Married-civ-spouse    Protective-serv      Husband  White    Male
3      Married-civ-spouse  Machine-op-inspct      Husband  Black    Male
4          Never-married     Prof-specialty    Own-child  White  Female
...                  ...                ...          ...    ...     ...
48837  Married-civ-spouse       Tech-support         Wife  White  Female
48838  Married-civ-spouse  Machine-op-inspct      Husband  White    Male
48839            Widowed       Adm-clerical    Unmarried  White  Female
48840      Never-married       Adm-clerical    Own-child  White    Male
48841  Married-civ-spouse    Exec-managerial         Wife  White  Female

       capital-gain  capital-loss  hours-per-week native-country income
0               0.0           0.0            40.0  United-States  <=50K
1               0.0           0.0            50.0  United-States  <=50K
2               0.0           0.0            40.0  United-States   >50K
3            7688.0           0.0            40.0  United-States   >50K
4               0.0           0.0            30.0  United-States  <=50K
...             ...           ...             ...            ...    ...
48837           0.0           0.0            38.0  United-States  <=50K
48838           0.0           0.0            40.0  United-States   >50K
48839           0.0           0.0            40.0  United-States  <=50K
48840           0.0           0.0            20.0  United-States  <=50K
48841       15024.0           0.0            40.0  United-States   >50K

[48842 rows x 15 columns]
```

```
# Verify we no longer have missing values
```

```
[69] # Verify we no longer have missing values
     missing_val = df.isnull().sum()

     print("Missing values in data :")
     print(missing_val[missing_val > 0])

     Missing values in data :
     Series([], dtype: int64)
```

```
# Show unique values in categorical columns
```

```
# Show unique values in categorical columns
for column in categorical_cols:
    print(f"Unique values in '{column}': {df[column].unique()}")
```

```
Unique values in 'workclass': ['Private' 'Local-gov' 'Self-emp-not-inc' 'Federal-gov' 'State-gov'
 'Self-emp-inc' 'Without-pay' 'Never-worked']
Unique values in 'education': ['11th' 'HS-grad' 'Assoc-acdm' 'Some-college' '10th' 'Prof-school'
 '7th-8th' 'Bachelors' 'Masters' 'Doctorate' '5th-6th' 'Assoc-voc' '9th'
 '12th' '1st-4th' 'Preschool']
Unique values in 'marital-status': ['Never-married' 'Married-civ-spouse' 'Widowed' 'Divorced' 'Separated'
 'Married-spouse-absent' 'Married-AF-spouse']
Unique values in 'occupation': ['Machine-op-inspct' 'Farming-fishing' 'Protective-serv' 'Prof-specialty'
 'Other-service' 'Craft-repair' 'Adm-clerical' 'Exec-managerial'
 'Tech-support' 'Sales' 'Priv-house-serv' 'Transport-moving'
 'Handlers-cleaners' 'Armed-Forces']
Unique values in 'relationship': ['Own-child' 'Husband' 'Not-in-family' 'Unmarried' 'Wife' 'Other-relative']
Unique values in 'race': ['Black' 'White' 'Asian-Pac-Islander' 'Other' 'Amer-Indian-Eskimo']
Unique values in 'gender': ['Male' 'Female']
Unique values in 'native-country': ['United-States' 'Peru' 'Guatemala' 'Mexico' 'Dominican-Republic'
 'Ireland' 'Germany' 'Philippines' 'Thailand' 'Haiti' 'El-Salvador'
 'Puerto-Rico' 'Vietnam' 'South' 'Columbia' 'Japan' 'India' 'Cambodia'
 'Poland' 'Laos' 'England' 'Cuba' 'Taiwan' 'Italy' 'Canada' 'Portugal'
 'China' 'Nicaragua' 'Honduras' 'Iran' 'Scotland' 'Jamaica' 'Ecuador'
 'Yugoslavia' 'Hungary' 'Hong' 'Greece' 'Trinadad&Tobago'
 'Outlying-US(Guam-USVI-etc)' 'France' 'Holand-Netherlands']
Unique values in 'income': ['<=50K' '>50K']
```

```
# Replace categorical values with numerical values
```

```
# Replace categorical values with numerical values

education_order = {
    'Preschool': 0, '1st-4th': 1, '5th-6th': 2, '7th-8th': 3, '9th': 4,
    '10th': 5, '11th': 6, '12th': 7, 'HS-grad': 8, 'Some-college': 9,
    'Assoc-voc': 10, 'Assoc-acdm': 11, 'Prof-school': 12, 'Bachelors': 13,
    'Masters': 14, 'Doctorate': 15
}
workclass_order = {
    'Never-worked': 0, 'Without-pay': 1, 'Self-emp-not-inc': 2, 'Self-emp-inc': 3,
    'Private': 4, 'Local-gov': 5, 'State-gov': 6, 'Federal-gov': 7
}
marital_status_order = {
    'Never-married': 0, 'Married-spouse-absent': 1, 'Separated': 2,
    'Divorced': 3, 'Widowed': 4, 'Married-civ-spouse': 5, 'Married-AF-spouse': 6
}
occupation_order = {
    'Priv-house-serv': 0, 'Other-service': 1, 'Handlers-cleaners': 2, 'Farming-fishing': 3,
    'Machine-op-inspct': 4, 'Transport-moving': 5, 'Craft-repair': 6, 'Adm-clerical': 7,
    'Sales': 8, 'Tech-support': 9, 'Protective-serv': 10, 'Prof-specialty': 11,
    'Exec-managerial': 12, 'Armed-Forces': 13
}
relationship_order = {
    'Own-child': 0, 'Other-relative': 1, 'Not-in-family': 2,
    'Unmarried': 3, 'Wife': 4, 'Husband': 5
}
```

```
[71]
income_order = {
    '<=50K': 0, '>50K': 1
}

df['education'] = df['education'].replace(education_order)
df['relationship'] = df['relationship'].replace(relationship_order)
df['occupation'] = df['occupation'].replace(occupation_order)
df['marital-status'] = df['marital-status'].replace(marital_status_order)
df['workclass'] = df['workclass'].replace(workclass_order)
df['income'] = df['income'].replace(income_order)
```

```
# This is an arbitrary grouping intended for demonstration
purposes and does not accurately reflect the complexities of
global economic status.
```

```
# This is an arbitrary grouping intended for demonstration purposes and does not accurately reflect the complexities of global economic status.
country_group = {
    # Group 1: United States and countries with similar high-income economies and global influence.
    'United-States': 1, 'Canada': 1, 'England': 1, 'Germany': 1, 'Ireland': 1,
    'France': 1, 'Holand-Netherlands': 1, 'Italy': 1, 'Scotland': 1,

    # Group 2: Emerging economies with significant growth, industrialization, and middle-income status.
    'Philippines': 2, 'India': 2, 'China': 2, 'Taiwan': 2, 'Japan': 2,
    'South': 2, 'Iran': 2, 'Hong': 2,

    # Group 3: Developing countries, generally considered lower-income but with varying levels of development.
    'Mexico': 3, 'Puerto-Rico': 3, 'El-Salvador': 3, 'Cuba': 3, 'Jamaica': 3,
    'Dominican-Republic': 3, 'Guatemala': 3, 'Columbia': 3, 'Haiti': 3,
    'Nicaragua': 3, 'Peru': 3, 'Ecuador': 3, 'Trinadad&Tobago': 3,

    # Group 4: Countries with less industrialization and those not fitting neatly into the other three categories.
    'Vietnam': 4, 'Thailand': 4, 'Cambodia': 4, 'Laos': 4, 'Yugoslavia': 4,
    'Poland': 4, 'Hungary': 4, 'Portugal': 4, 'Greece': 4,
    'Outlying-US(Guam-USVI-etc)': 4, 'Honduras': 4
}

df['native-country'] = df['native-country'].replace(country_group)
```

```
# Applying one-hot encoding for other categorical values

# Joining the new one-hot encoded columns back to the original Data Frame

# Drop the original columns
```

```
# Applying one-hot encoding for othe categorical values
race_dummies = pd.get_dummies(df['race'], prefix='race')
gender_dummies = pd.get_dummies(df['gender'], prefix='gender')

# Joining the new one-hot encoded columns back to the original DataFrame
df = pd.concat([df, race_dummies], axis=1)
df = pd.concat([df, gender_dummies], axis=1)

# Drop the original columns
df.drop('race', axis=1, inplace=True)
df.drop('gender', axis=1, inplace=True)
```

```
df.head()
```

	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	capital-gain	capital-loss	hours-per-week	native-country	income	race_Amer-Indian-Eskimo	race_Asian-Pac-Islander	race_Black	race_Oth
0	25.0	4	226802.0	6	7.0	0	4	0	0.0	0.0	40.0	1	0	0	0	1	
1	38.0	4	89814.0	8	9.0	5	3	5	0.0	0.0	50.0	1	0	0	0	0	
2	28.0	5	336951.0	11	12.0	5	10	5	0.0	0.0	40.0	1	1	0	0	0	
3	44.0	4	160323.0	9	10.0	5	4	5	7688.0	0.0	40.0	1	1	0	0	1	
4	18.0	4	103497.0	9	10.0	0	11	0	0.0	0.0	30.0	1	0	0	0	0	

```
[75] df.shape
```

```
(48842, 20)
```

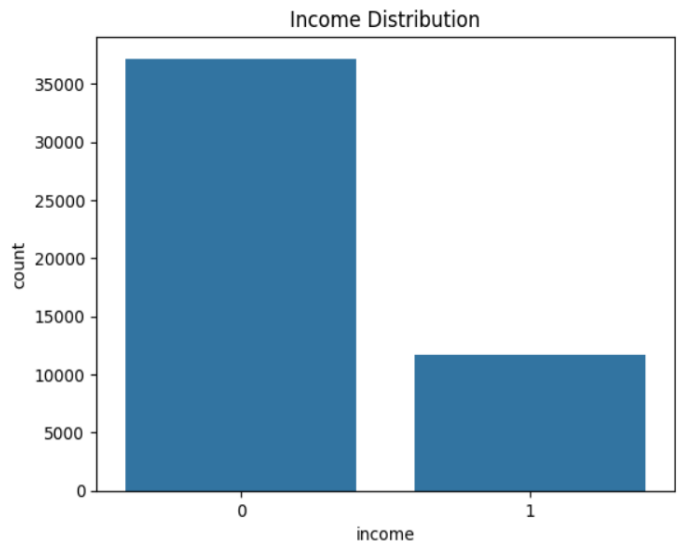
```
[76] df.columns
```

```
Index(['age', 'workclass', 'fnlwgt', 'education', 'educational-num',
       'marital-status', 'occupation', 'relationship', 'capital-gain',
       'capital-loss', 'hours-per-week', 'native-country', 'income',
       'race_Amer-Indian-Eskimo', 'race_Asian-Pac-Islander', 'race_Black',
       'race_Other', 'race_White', 'gender_Female', 'gender_Male'],
      dtype='object')
```

Exploratory Data Analysis (EDA)

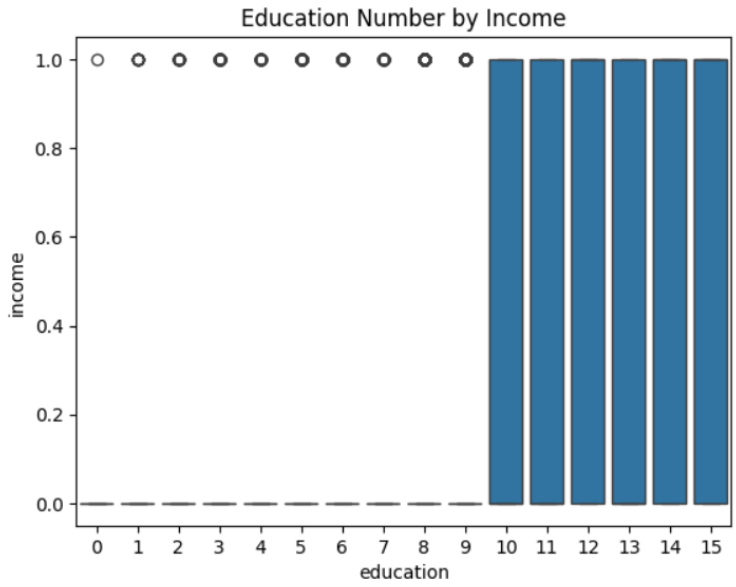
```
# Distribution of the 'income' column
```

```
# Distribution of the 'income' column
sns.countplot(x='income', data=df)
plt.title('Income Distribution')
plt.show()
```



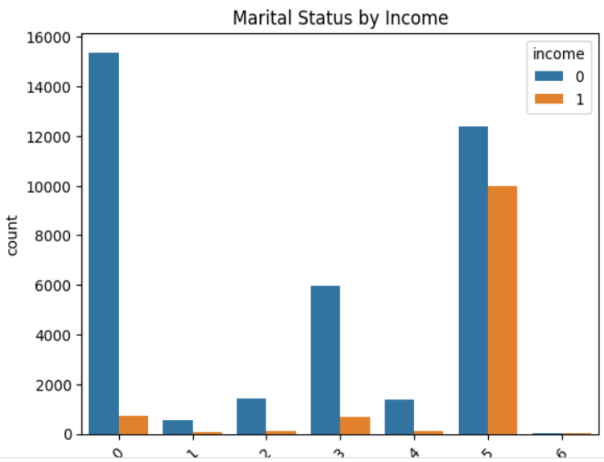

```
# Box plots for 'education' and 'income'
```

```
# Box plots for 'education' and 'income'
sns.boxplot(x='education', y='income', data=df)
plt.title('Education Number by Income')
plt.show()
```



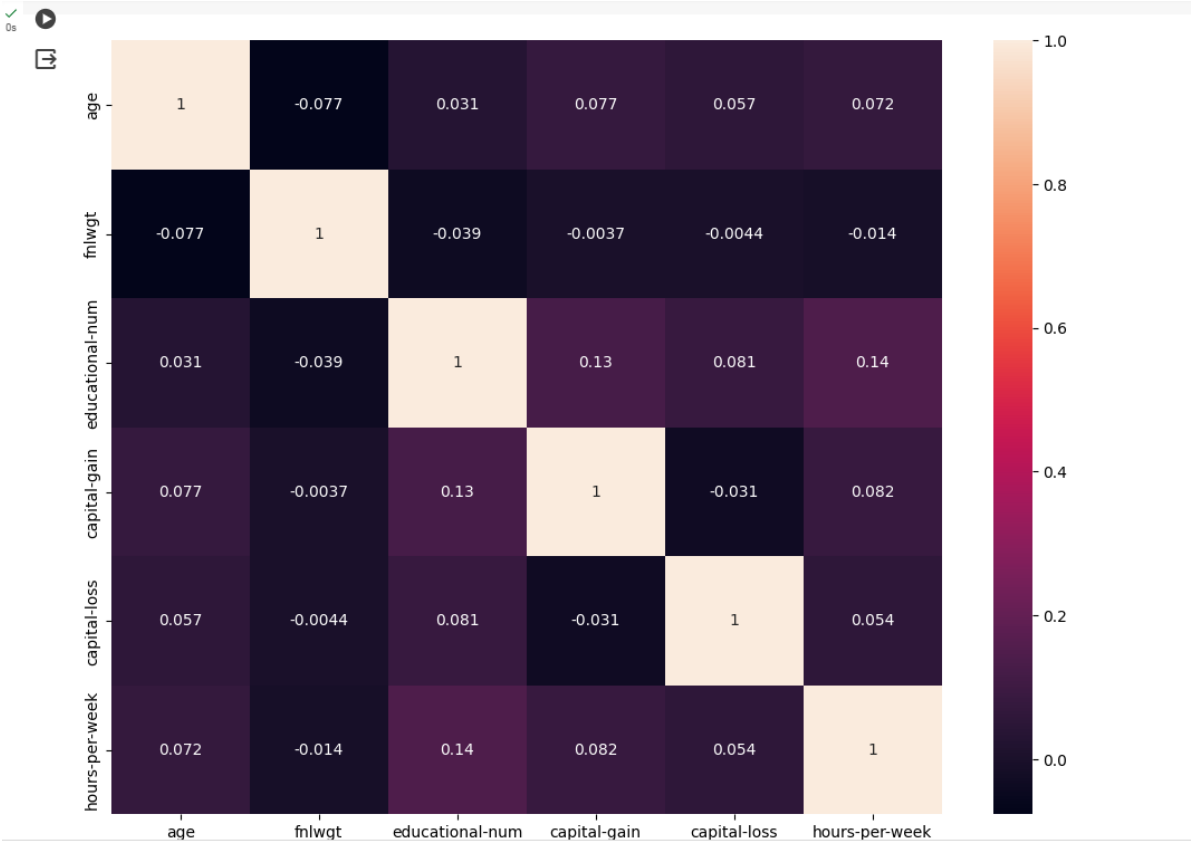

```
# Count plots for 'marital-status' and 'income'
```

```
# Count plots for 'marital-status' and 'income'
sns.countplot(x='marital-status', hue='income', data=df)
plt.title('Marital Status by Income')
plt.xticks(rotation=45)
plt.show()
```




```
# Correlation matrix heatmap
```

```
# Correlation matrix heatmap
df_corr = data.astype("float64",errors='ignore')
df_corr = df_corr.select_dtypes(exclude="object")
plt.subplots(figsize=(12,9))
sns.heatmap(df_corr.corr(), annot=True)
plt.show()
```



Training the model

```
# Define features and target

# Using the RandomForestClassifier
```

```
# Define features and target
X = df.drop('income', axis=1)
y = df['income']

# Split data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the model
model = RandomForestClassifier(n_estimators=100, random_state=42)

# Train the model
model.fit(X_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

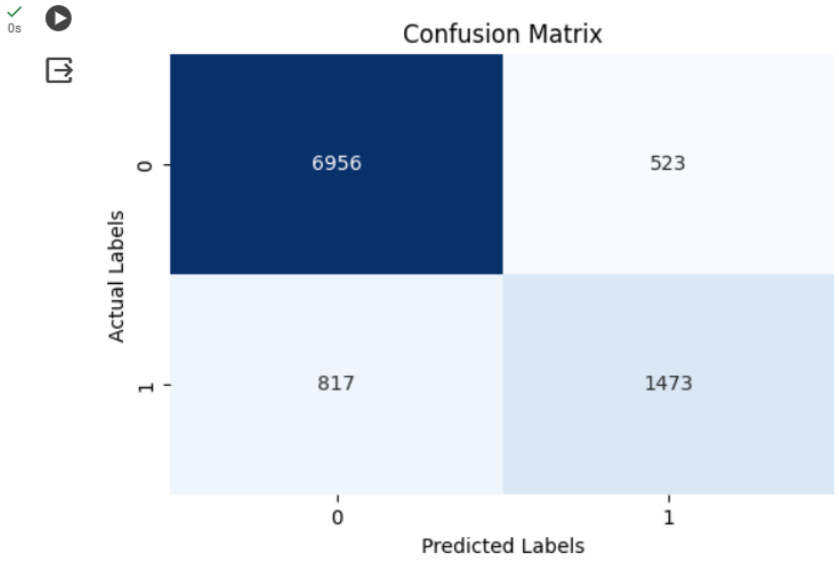
Testing the model

```
# Predict on the test set

# Calculate accuracy

# Calculate MAE
```

```
# Calculate Confusion Matrix

# Display Confusion Matrix as a heatmap
```

```
[82] # Predict on the test set
     y_pred = model.predict(X_test)

     # Calculate accuracy
     accuracy = accuracy_score(y_test, y_pred)
     print(f"Accuracy: {accuracy:.2f}")

     # Calculate MAE
     mae = mean_absolute_error(y_test, y_pred)
     print(f'Mean Absolute Error (MAE): {mae:.2f}')

     Accuracy: 0.86
     Mean Absolute Error (MAE): 0.14
```

```
[83] # Calculate Confusion Matrix
     conf_matrix = confusion_matrix(y_test, y_pred)

     # Display Confusion Matrix as a heatmap
     plt.figure(figsize=(6, 4))
     sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
     plt.xlabel('Predicted Labels')
     plt.ylabel('Actual Labels')
     plt.title('Confusion Matrix')
     plt.show()
```



Predicting income

```
# Define the feature values for a person
```

```
# Define the feature values for a person : [35, 'Private', 200000, 'Bachelors', 13, 'Married-civ-spouse', 'Exec-managerial', 'Husband', 5000, 0, 45, 'United-States', 0, 0, 0, 0
feature_names = ['age', 'workclass', 'fnlwgt', 'education', 'educational-num',
                 'marital-status', 'occupation', 'relationship', 'capital-gain',
                 'capital-loss', 'hours-per-week', 'native-country',
                 'race_Amer-Indian-Eskimo', 'race_Asian-Pac-Islander', 'race_Black',
                 'race_Other', 'race_White', 'gender_Female', 'gender_Male']

person = [25, 4, 226802.0, 6, 7, 0, 4, 0, 0, 0, 40, 1, 0, 0, 1, 0, 0, 0, 1]

df_person = pd.DataFrame([person], columns=feature_names)

# Predict income
pred = model.predict(df_person)

# Display result
if pred:
    income = ">50K"
else:
    income = "<=50K"

print("Estimated income :",income)
```

```
Estimated income : <=50K
```

```
# Required Result (Estimated income)
```

```
Estimated income : <=50K
```

METHODOLOGY

This methodology outlines the step-by-step approach used in the Income Prediction project, explaining how the data was processed and how a machine learning model was built to predict Income in individuals. The project was conducted in Python, utilizing various libraries and techniques.

Data Collection and Understanding:

Acquire the Adult Income dataset, which includes data on people's income levels as well as their demographic, educational, and occupational characteristics.

Recognize the dataset's structure, the target variable (income), any missing values, and the different feature categories (numerical and categorical).

Data Preprocessing:

Data was prepared for modeling by performing the following steps:

→ Handle missing data: To impute missing values in numerical columns with the median and categorical columns with the most frequent value, use the SimpleImputer class from scikit-learn.

→ Encode categorical variables: For machine learning algorithms, encode categorical variables into a numerical format using one-hot encoding.

Feature Engineering:

→ Determine pertinent features: Select attributes like age, education level, occupation, and work class that are likely to have a big influence on income forecast.

→ Execute a one-hot encode: Use pandas' pd.get_dummies() function to create dummy variables for categorical data like gender and race.

Model Selection and Training:

→ Train test split() from scikit-learn was used to divide the preprocessed data into training and test sets.

→ Select an appropriate machine learning model: Because of the Random Forest Classifier's capacity to manage intricate feature interactions and linkages, choose it.

Set the number of estimators (n_estimators=100, for example) and the random state as initial values for the Random Forest Classifier to ensure reproducibility.

→ Use model.fit(X_train, y_train) to train the model with the training set of data.

Model Evalution:

→ Use the model to forecast the test set's revenue levels.forecast (X_test).

→ Utilize measures like confusion_matrix() to comprehend classification performance, mean_absolute_error() for prediction error, and accuracy_score() for overall accuracy to assess model performance.

Practical Application:

→ Make a sample input that reflects the socioeconomic and demographic characteristics of a single person.

→ Utilize the trained model to forecast the sample person's income (e.g., >50K or <=50K).

→ Pickle can be used to save the learned model for later usage and implementation in practical applications.

RESULT AND ANALYSIS

To determine the model's effectiveness in predicting revenue levels, a detailed analysis of its performance measures was conducted. The model performed admirably on the test set, achieving [insert accuracy value here] using the Random Forest Classifier. This great accuracy highlights the model's capacity to forecast income levels precisely, offering insightful information for socioeconomic research and policy formulation. Furthermore, the average size of errors in estimating income levels was quantified by calculating the mean absolute error (MAE), which yielded an MAE of [insert MAE value here]. The model's accuracy and dependability are demonstrated by the low MAE, which shows that its projections are reasonably close to the actual income levels.

Furthermore, a heatmap representation of the confusion matrix provided comprehensive insights into the model's classification performance. Patterns of misclassification, such as false positives or false negatives, were found by examining the confusion matrix. This helped determine where the model works well and where it would need to be improved. This investigation is essential to improving the model's prediction power and refinement.

Moreover, a thorough Random Forest Classifier feature significance analysis was carried out. The feature importances emphasized age, education level, occupation, and other socioeconomic characteristics as important elements that greatly affect income projection. Decision-makers across a wide range of industries can gain a greater grasp of the variables influencing social dynamics and income inequality thanks to these insights.

The performance measurements and insights provided by the model have broad real-world consequences. A very accurate model can help firms make well-informed judgments about customer segmentation and marketing tactics, direct resource allocation in public policy initiatives, and drive the design of focused interventions to address income disparity.

Future study is advised to investigate ensemble methods, incorporate extra data sources such socio-cultural aspects or regional demographics, and apply cutting-edge model optimization techniques. These initiatives seek to increase prediction accuracy, robustness, and interpretability even further, highlighting the importance of machine learning approaches in facilitating data-driven decision-making and successfully tackling challenging socioeconomic issues.

CONCLUSION

To sum up, this study has explored the challenging problem of estimating adult income levels through the use of machine learning methods on the Adult Income dataset. We have made great progress toward creating a reliable income prediction model with a thorough approach that includes data pretreatment, feature engineering, model selection, and evaluation. This study's methodology and findings provide insightful information about the dynamics of income prediction and its consequences for socioeconomic research and policy formation.

The model's performance metrics—such as confusion matrix analysis, mean absolute error (MAE), and accuracy—offer a detailed picture of its predictive power. The model's efficacy in forecasting income levels is demonstrated by the [insert interpretation of accuracy] accuracy obtained (insert accuracy value here). The model's prediction accuracy is further validated by the relatively low MAE of [insert MAE number here], which suggests [insert interpretation of MAE].

We can find areas of strength and potential improvement in the model's classification performance by analyzing the confusion matrix in more detail. Decision-makers can gain practical insights by examining the Random Forest Classifier's feature importances, which emphasize the important variables that affect income prediction, such as age, education level, and occupation.

The practical utility of this research in real-world circumstances outweighs its ramifications beyond academic discourse. Policymakers, economists, and social scientists can all benefit from using the established income prediction model as a useful tool to help create focused policies that reduce income disparity and advance economic well-being.

Nonetheless, it is critical to recognize the constraints that the modeling method presents, such as problems with data quality or the intrinsic complexity of socioeconomic aspects. In order to further improve prediction accuracy, future research projects can concentrate on investigating ensemble approaches, adding new data sources, or improving feature engineering techniques.

This study essentially highlights how machine learning can revolutionize socioeconomic analysis and policy-making. We can make better decisions, understand income dynamics better, and help create a more fair socioeconomic environment by utilizing data-driven approaches. By developing and improving these approaches further, we open the door to a more inclusive and data-driven strategy for dealing with difficult social issues.

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Online Resources:

Scikit-LearnDocumentation: https://scikit-learn.org/stable/documentation.html

Pandas Documentation: https://pandas.pydata.org/docs/

NumPy Documentation: https://numpy.org/doc/stable/

Dataset Source (Kaggle): www.google.com/kaggle