INSURANCE POLICY PREDICTION AND FRAUD DETECTION SYSTEM.

DONE BY

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Abstract

This project aims to develop a comprehensive system for insurance prediction with two primary functionalities: premium calculation for common people and fraud detection for insurance agents. Common users can input their vehicle and personal details to receive accurate premium amount predictions, while insurance agents will utilize the system to predict whether submitted claims are fraudulent. The objective is to enhance the transparency and efficiency of insurance-related processes by leveraging machine learning techniques for both premium estimation and fraud detection.

Existing insurance systems often rely on manual and traditional processes, which are time-consuming and prone to errors. For premium calculations, customers are usually presented with rigid plans without considering personalized risk factors. Similarly, fraud detection methods lack the agility and precision needed to identify anomalies in a large volume of claims. This project addresses these gaps by using data-driven predictions, automating tasks, and providing real-time insights for both customers and agents.

The proposed development is divided into two key modules. **The first module is designed for consumers**, where users input their data (e.g., vehicle details, driving history), and the system computes a customized premium amount based on the provided information. **The second module is for insurance agents** to input claim details and receive predictions on whether the claim is likely to be fraudulent. **Deep learning algorithms** such as **LSTM** for time-dependent data, **Feedforward Neural Networks** for structured data, **Autoencoders** for anomaly detection, and **Gradient Boosted Neural Networks** for enhancing prediction accuracy are utilized to ensure high performance.

This project will utilize **Python** as the primary programming language, leveraging libraries such as **Pandas** for data manipulation, **Scikit-learn** for machine learning, and **Matplotlib or Seaborn** for visualization. The **Streamlit framework** will be employed for creating the interactive web application, ensuring ease of access and usability for stakeholders. The final outcome will be a user-friendly and efficient platform that aids consumers in making informed insurance decisions while helping agents streamline the fraud detection process.

Problem Statement :

In the modern insurance landscape, figuring out the right insurance premiums and spotting fraudulent claims is crucial for both customers and insurers. However, traditional methods often struggle with the growing complexity and sheer volume of data, making it hard for insurance companies to make smart decisions. Our project aims to tackle this issue by developing a cutting-edge system that leverages deep learning technologies. This system will help everyday people

estimate their insurance premiums based on details about their vehicles and driving habits. Simultaneously, it will provide insurance agents with tools to identify potentially fraudulent claims. By effectively analyzing both time-sensitive and structured data, we hope to enhance prediction accuracy and offer valuable insights for both policyholders and insurance providers.

Outcome :

- **Predicting Insurance Premiums:** We aim to create a model that accurately forecasts insurance premiums based on user data, such as vehicle details and claims history, using advanced deep learning techniques like LSTM and Feedforward Neural Networks.
- **Detecting Fraudulent Claims:** Our goal is to develop a system that effectively identifies fraudulent claims by analyzing unusual patterns in claims data with tools like Autoencoders and Gradient Boosted Neural Networks, helping insurance agents make informed decisions.
- **Creating a User-Friendly Web Application:** We will build an intuitive web application using Streamlit, allowing users to easily input their information for premium predictions while providing insurance agents with tools to assess potential fraud.
- **Visualizing Data Insights:** We will incorporate data visualization tools like Matplotlib and Seaborn to present our findings clearly, enabling users to understand predictions and insights for better decision-making.

Datasets

Dataset Name: Vehicle Insurance Fraud Detection

Dataset Link :

https://www.kaggle.com/datasets/omegasemmalaicit/insurance-policy-and-fraud-prediction

The project will utilize two primary datasets: the **"Fraud Detection "** dataset. These datasets collectively provide a comprehensive view of Fraudulent claims and the premium amount, offering essential insights into the factors contributing to claims.

Fraud Detection Dataset : The Fraud Detection Dataset contains information about insurance claims and their characteristics. This dataset is crucial for analyzing factors associated with fraudulent claims. It includes the following columns:

Month: The month when the claim occurred.

WeekOfMonth: The week of the month when the claim occurred.

DayOfWeek: The day of the week when the claim occurred.

Make: The make of the vehicle involved in the claim.

AccidentArea: The area where the accident occurred.

DayOfWeekClaimed: The day of the week the claim was filed.

MonthClaimed: The month when the claim was filed.

WeekOfMonthClaimed: The week of the month when the claim was filed.

Sex: The gender of the policyholder.

MaritalStatus: The marital status of the policyholder.

Age: The age of the policyholder.

Fault: Indicates who was at fault in the accident (e.g., Third Party).

PolicyType: The type of insurance policy (e.g., Liability, Collision).

VehicleCategory: The category of the vehicle (e.g., Sedan, Utility).

VehiclePrice: The price of the vehicle.

ClaimAmount: The amount claimed.

PolicyNumber: The unique number identifying the insurance policy.

RepNumber: The representative number associated with the claim.

Deductible: The deductible amount for the policy.

DriverRating: The rating of the driver (risk assessment).

Days: The number of days between policy purchase and accident.

Days: The number of days between policy purchase and claim filing.

PastNumberOfClaims: The number of claims filed in the past.

AgeOfVehicle: The age of the vehicle involved in the claim.

AgeOfPolicyHolder: The age of the policyholder.

PoliceReportFiled: Indicates if a police report was filed (Yes/No).

WitnessPresent: Indicates if a witness was present (Yes/No).

AgentType: The type of agent handling the claim (e.g., Internal, External).

NumberOfSuppliments: The number of supplements for the claim.

AddressChange-Claim: Indicates if there was an address change for the claim (Yes/No).

NumberOfCars: The number of cars involved in the claim.

Year: The year when the claim occurred.

BasePolicy: The base policy under which the claim was filed.

FraudFound: Indicates if fraud was detected (Yes/No).

Literature Survey :

In recent years, the application of machine learning (ML) in analyzing vehicle insurance claims and detecting potential fraud has gained significant attention.

Wang et al. [1] introduced a framework that uses predictive modeling with claims data to identify fraudulent activities. Their study highlighted the effectiveness of random forest classifiers, which achieved high accuracy in detecting fraud, potentially transforming how the insurance industry approaches fraud detection.

Smith et al. [2] explored a different approach by using deep learning techniques, specifically convolutional neural networks (CNNs), to analyze images from accident scenes. Their research showed that CNNs could validate claims by analyzing photographic evidence, offering a new way to detect fraud beyond traditional data analysis methods.

Another study by Brown and Green [3] focused on improving the prediction accuracy for claim amounts by using ensemble learning methods. They combined various ML models, such as gradient boosting and decision trees, and found that this blend outperformed individual models, which is a promising insight for insurers seeking to optimize their claims processes.

Kumar [4] looked into demographic and behavioral factors that might influence fraudulent claims. Their findings suggest that certain customer profiles are more likely to engage in fraudulent activities, providing insurers with valuable information to create targeted prevention strategies.

Zhang and Liu [5] proposed an unsupervised learning approach for detecting anomalies in claims data. This method helps to identify unusual patterns, making it easier for insurers to flag suspicious claims for further investigation.

Chen [6] tackled the issue of imbalanced datasets in fraud detection. By using synthetic data generation techniques, they demonstrated how balancing training data can enhance the performance of classifiers in identifying fraudulent claims.

Johnson and Lee [7] used natural language processing (NLP) to analyze text descriptions in insurance claims. Their work showed that sentiment analysis could reveal inconsistencies in claims, which is helpful in spotting potential fraud.

Moore [8] examined how geographical information systems (GIS) could be used in claims analysis, revealing that spatial analysis could identify fraud patterns in specific areas. This approach can help insurers allocate resources more efficiently for investigations.

Zhang and Liu [9] also discussed how blockchain technology could improve transparency and security in insurance transactions. They highlighted that blockchain's immutable record-keeping could significantly reduce fraud, providing a new level of trust and accountability in the claims process.

Wilson [10] explored the impact of customer feedback and reviews on assessing the reliability of insurance claims. By analyzing data from social media, they found that insurers could use public opinions to identify potentially fraudulent claims based on community feedback.

A study on forecasting motor insurance claims [11] utilized machine learning models like Random Forest and XGBoost, incorporating weather conditions and car sales data from Athens, Greece, over the period 2008-2020. By focusing on key predictors such as lagged car sales and minimum temperature, the study achieved high accuracy, offering insurers enhanced capabilities for predicting claims and managing risks effectively.

Overall, these studies emphasize the growing importance of machine learning and advanced analytics in the insurance industry. They highlight how innovative approaches, such as using image analysis, NLP, and blockchain, can help insurers detect fraud more effectively and improve the overall claims process.

Advantages:

1. **High Accuracy:** Machine learning models, particularly random forest classifiers, have demonstrated high accuracy in detecting fraudulent insurance claims, making them a reliable tool for insurers.
2. **Enhanced Fraud Detection:** Deep learning techniques, such as convolutional neural networks (CNNs), significantly improve fraud detection capabilities by analyzing visual data from accident scenes, adding a new layer of validation.
3. **Better Predictions:** Utilizing ensemble methods that combine multiple models can yield more accurate predictions of insurance claim amounts compared to relying on single models, thus enhancing decision-making.
4. **Targeted Fraud Prevention:** Insights gained from understanding demographic factors can help create specific strategies for fraud prevention tailored to different customer profiles, making efforts more effective.
5. **Actionable Insights:** Unsupervised learning methods can identify unusual patterns in claims data, providing insurers with valuable insights that prompt further investigation and enhance fraud detection strategies.

Disadvantages:

1. **Data Preparation Challenges:** Many machine learning models require extensive data cleaning and preparation, which can be labor-intensive and time-consuming, potentially delaying implementation.
2. **Computational Costs:** Advanced machine learning models, especially deep learning techniques, often demand significant computational resources, leading to higher operational costs for insurers.

3. **Complexity of Models:** The use of multiple combined models can complicate the implementation process and require more resources for management, making it challenging to maintain and deploy effectively.
4. **False Positives:** Anomaly detection methods may incorrectly flag legitimate claims as fraudulent, resulting in unnecessary investigations and potentially damaging customer relationships.

References

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MODELS CHOSEN :

LSTM (Long Short-Term Memory) for Time-Dependent Data

- LSTMs are good at working with data that changes over time, like sequences or trends.
- In our dataset, we have features like **Month**, **WeekOfMonth**, and **DayOfWeek**. These can help us understand patterns in accidents or claims that happen at different times.
- LSTMs can remember important information from the past while forgetting things that aren't useful. This helps us predict what might happen in the future.

Feedforward Neural Networks for Structured Data

- Feedforward Neural Networks (FNNs) work well with organized data where we have clear input features and outputs.
- Our dataset has a mix of numbers and categories, like **VehiclePrice** and **PolicyType**. FNNs can learn from all these different types of data.
- They are great at figuring out complex relationships, which helps us predict things like whether a claim is fraudulent or what policy might be.

Autoencoders for Anomaly Detection

- Autoencoders are special models that learn to understand what normal data looks like.
- They can help us find unusual data, like strange claim amounts that could mean fraud.
- Autoencoders can also make our data simpler to work with, which is helpful when we have a lot of information.

Gradient Boosted Neural Networks (GBNN) for Predictive Modeling

- GBNN is a strong method that combines many simple models (like small decision trees) to make better predictions.
- Our data might not have equal amounts of fraud and non-fraud cases. GBNN can handle this problem well and give us more accurate results.
- GBNN can show us which features are important, helping us understand what causes fraud or affects claims.
- Since we have a large dataset with 150,000 records, GBNN is efficient and can work well with this amount of data.

MODEL EXPLANATION :

LSTM (Long Short-Term Memory)

- LSTM is a special kind of network that is really good at understanding and predicting data that changes over time.
- **Working**: It has memory cells that can remember information for a long time. LSTMs use gates to control what information to keep and what to forget. This is important for figuring out what might happen in the future based on past data, which makes LSTM great for tasks like predicting events over time.

Feedforward Neural Networks (FNN)

- FNNs are basic networks used for different types of predictions.
- **Working**: In an FNN, data moves in one direction—from the input layer to hidden layers and then to the output layer. Each part of the network does some calculations using the data it gets. This helps the model learn how different features (like **VehiclePrice** and **ClaimAmount**) are related to each other and make predictions (like whether a claim is fraudulent). FNNs work well with structured data.

Autoencoders

- Autoencoders are used for learning from data without needing labels, mainly for finding unusual patterns.
- **Working**: An autoencoder has two main parts: an encoder that shrinks the input data to a smaller size and a decoder that tries to rebuild the original data. While training, it learns to make the output as close to the input as possible. If it sees something unusual (like a strange claim), it can't rebuild it well, which shows that it might be an anomaly.

Gradient Boosted Neural Networks (GBNN)

- GBNNs are models that improve their predictions by combining the results of several weaker models (like decision trees).
- **Working:**The model builds trees one after the other. Each new tree tries to fix the mistakes made by the previous trees. By paying more attention to the errors, GBNNs get better at making accurate predictions over time. They work well with different types of data and are good for tasks like fraud detection.

MODEL METRICS :

Model	Metrics	Hyperparameter Tuning
LSTM	1. MSE/RMSE 2. AUC-ROC 3. Accuracy	1. Number of layers 2. Number of units per layer 3. Dropout rate 4. Optimizer
Autoencoders	1. MSE/RMSE 2. AUC-ROC 3. Accuracy	1. Number of hidden layers 2. Number of neurons per layer 3. Learning rate Activation function 4. Batch size 5. Loss function
Feed-Forward Neural Networks	1. MSE/RMSE 2. AUC-ROC 3. Accuracy	1. Number of hidden layers 2. Number of neurons per layer 3. Number of Epochs for Training 4. Activation function 5. Batch size
Gradient Boost Neural Networks	1. MSE/RMSE 2. AUC-ROC 3. Accuracy	1. Number of neurons in hidden layer 2. Number of epochs for training 3. Size of the batches for training 4. Learning rate 5. Dropout rate

MODEL DEVELOPMENT :

EXPLORATORY DATA ANALYSIS :

1. Import Libraries

- Start by importing essential libraries such as Pandas for data handling, NumPy for numerical operations, Matplotlib and Seaborn for data visualization, and scikit-learn for model training and evaluation.

2. Load Data

- Load the dataset from a CSV file using Pandas. This dataset contains various features that will help in predicting the target variable, FraudFound and Policy type.

3. Display Basic Information

- Check the basic information of the dataset, including data types and non-null counts, to understand its structure and the types of variables available.

4. Handle Missing Values

- Identify and handle any missing values in the dataset. In this case, rows with missing values are dropped to ensure a clean dataset for analysis.

5. Conduct Exploratory Data Analysis (EDA) :

1. Visualizing the Distribution of the Target Variable:

- Create a count plot for the target variable, FraudFound, to visualize the balance between fraudulent (1) and non-fraudulent claims (0). This helps assess class distribution and informs potential strategies for handling class imbalance.

2. Analyzing the Distribution of Numerical Features:

- Use histograms to explore the distribution of numerical features, highlighting the central tendency and spread of the data. Understanding these distributions can indicate if any features require transformation to meet model assumptions.

3. Outlier Detection:

- Generate box plots to identify outliers in numerical features. Outliers are data points significantly different from the rest and can impact model training. Knowing how to handle them is crucial for effective modeling.

4. Correlation Analysis:

- Examine the correlation between numerical features and the target variable using a heatmap. Identifying highly correlated features can guide feature selection and highlight potential predictors for the model.

5. Categorical Feature Analysis:

- Visualize categorical features using bar plots to understand the frequency of different categories. Analyzing the relationship between these categories and the target variable can reveal insights into factors that influence fraud.

GRADIENT BOOSTED NEURAL NETWORK :

Initial model building steps :

1. **Import Libraries**: First, you need to import some important libraries. You'll want to use NumPy for doing math stuff, pandas for handling your data, TensorFlow/Keras for making the neural network, and scikit-learn to help you evaluate your model.
2. **Load Data**: Next, load your dataset from a CSV file. This dataset should have a bunch of features that you will use to predict your target variable, which is PolicyType and Fraud found.

3. **Separate Features and Target**: Once the data is loaded, split it into two parts: the features (the stuff you'll use to train the model) and the target variable (which is PolicyType and Fraud Found). The features are the input, and the target is what you're trying to predict.
4. **Split Data**: After that, split your dataset into a training set and a testing set. Usually, you take 80% for training and 20% for testing. This way, you can train the model on one part and check how well it works on another part.
5. **Define the Neural Network**: Now, create your neural network model. This will have an input layer, one or more hidden layers, and an output layer. Use activation functions like ReLU for the hidden layers and sigmoid for the output layer since you're doing a multiclass classification.
6. **Train the Model**: Finally, train your model using the training data. Keep an eye on how it's doing over multiple epochs, adjusting the weights to reduce errors. Make sure to check the model's performance on the training set while it's learning to see if it's getting better.

Hyperparameter Tuning Steps

1. **Set Up Hyperparameter Tuning**: First, figure out which hyperparameters you need to tune. This might include the number of neurons in each layer, dropout rates (to avoid overfitting), and learning rates (to control how fast the model learns).
2. **K-Fold Cross-Validation**: Next, use k-fold cross-validation. This means you'll split your training data into k subsets and train your model k times. Each time, use a different subset for validation and the rest for training. It helps to make your model evaluation stronger.
3. **Early Stopping**: Also, set up early stopping while training. This checks the validation loss, and if it doesn't improve after a certain number of epochs ,the training stops to prevent overfitting.
4. **Select Best Hyperparameters**: After you finish the k-fold cross-validation, look at the accuracy results. Find out which set of hyperparameters worked the best and gave you the highest average accuracy. This helps you choose the best model setup.
5. **Train Final Model**: Now, with the best hyperparameters you found, retrain your model using the whole training dataset. Keep using early stopping to make sure your training is on point.
6. **Test Final Model**: Lastly, test your trained model on the test dataset. Use important performance metrics like accuracy, mean squared error (MSE), mean absolute error (MAE), and ROC AUC score. This will show you how well your hyperparameter tuning worked and how good your model is overall.

FEED FORWARD NEURAL NETWORK

Initial Model Building Steps :

1. **Import Libraries:** Start by importing important libraries. You'll need NumPy for mathematical operations, pandas for data handling, TensorFlow/Keras to build the neural network, and scikit-learn for evaluating the model.
2. **Load Data:** Load your dataset from a CSV file using pandas. This dataset should contain various features that will help you predict your target variable, which is FraudFound and Policytype
3. **Clean Column Names:** Make sure to clean up any extra spaces in the column names to avoid issues later.
4. **One-Hot Encode Categorical Columns:** If you have any categorical columns (like strings), you should convert them into numerical format using one-hot encoding. This makes it easier for the neural network to understand.
5. **Prepare Features and Target:** Once your data is ready, split it into features (the inputs) and the target variable (FraudFound & Policy type). The features will be used for training, while the target is what you are trying to predict.
6. **Split Data:** Divide your dataset into training and testing sets. Usually, you'll use 80% of the data for training and 20% for testing. This way, you can train the model on one set and evaluate its performance on another.
7. **Normalize Features:** Normalize your features to make sure they are on the same scale. This helps the model learn better. You can use StandardScaler from scikit-learn for this.
8. **Define the Neural Network:** Create your neural network model using Sequential. Add an input layer, one or more hidden layers, and an output layer. Use activation functions like ReLU for the hidden layers and sigmoid for the output layer since you are doing binary classification.
9. **Train the Model:** Train your model using the training data. Keep track of its performance over multiple epochs (iterations). Make sure to validate the model on a part of the training set during this time.
10. **Evaluate the Model:** After training, evaluate the model on the test set to see how well it performs. You can get metrics like accuracy to understand its effectiveness.
11. **Calculate Additional Metrics:** Calculate other important metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and ROC AUC score to get a more comprehensive view of the model's performance.

Hyperparameter Tuning Steps

1. **Set Up Hyperparameter Tuning:** Identify the hyperparameters you want to tune, like the number of neurons in each layer, dropout rates, and learning rates.

2. **Define the Model Building Function:** Create a function that builds the model with the ability to change hyperparameters. You can adjust the number of layers and the number of neurons in each layer based on your tuning.
3. **Set Up the Tuner:** Use a hyperparameter tuning library (like keras_tuner) to search for the best combination of hyperparameters. This involves running the model multiple times with different configurations.
4. **K-Fold Cross-Validation:** Optionally, implement k-fold cross-validation to get a better evaluation of your model. This involves splitting the training data into several subsets and training the model multiple times on different combinations of these subsets.
5. **Early Stopping:** During training, implement early stopping to prevent overfitting. This checks if the model's performance on a validation set is improving, and if not, it stops training early.
6. **Select Best Hyperparameters:** After the tuning process, analyze the results to find which set of hyperparameters performed the best based on validation accuracy.
7. **Train Final Model:** With the best hyperparameters identified, retrain your model using the entire training dataset.
8. **Test Final Model:** Finally, evaluate the tuned model on the test dataset to check its performance. Again, use various metrics like accuracy, MSE, MAE, RMSE, and ROC AUC to see how well it works.

LSTM - (LONG SHORT TERM MEMORY)

Initial Model Building Steps:

1. **Import Libraries**: Begin by importing the necessary libraries. Use pandas for data manipulation, numpy for numerical computations, scikit-learn for machine learning functionalities like data splitting and preprocessing, and TensorFlow/Keras for building and training the LSTM model.
2. **Load Data**: Load the dataset from a CSV file. This dataset should contain features relevant to predicting the target variables: PolicyType (the primary target) and FraudFound (a secondary target indicating whether fraud was detected).
3. **Separate Features and Targets**: After loading the data, separate it into two parts: the features (inputs used for training the model) and the target variables (PolicyType and FraudFound).
4. **Split Data**: Divide the dataset into training and testing sets. A common practice is to allocate 80% of the data for training and 20% for testing, ensuring a proper assessment of the model's performance on unseen data.

5. **Encode Categorical Features**: Convert categorical variables into numeric representations using LabelEncoder to prepare the data for the neural network, allowing the model to interpret the input data correctly.
6. **Standardize Features**: Apply StandardScaler to normalize the feature values. This step is essential for neural networks, as it helps speed up convergence and improve overall model performance.
7. **Reshape Data for LSTM**: Transform the training and testing feature sets into the appropriate shape for the LSTM model. LSTMs require input in the form of [samples, time steps, features].
8. **Define the Model**: Create the LSTM model architecture, which should include layers such as LSTM units, dropout layers for regularization, and a final dense layer with a softmax activation function for multi-class classification of PolicyType (and a sigmoid activation function for binary classification of FraudFound if applicable).
9. **Train the Model**: Train the model using the training data. Monitor performance through multiple epochs, adjusting the weights to minimize loss. Validation should be performed using a portion of the training data.

Hyperparameter Tuning Steps:

1. **Set Up Hyperparameter Tuning**: Identify the key hyperparameters to tune, which include the number of LSTM units in each layer, the dropout rates for dropout layers to prevent overfitting, and the learning rate that controls the speed of learning.
2. **Use Keras Tuner for Random Search**: Implement Keras Tuner's Random Search to explore various combinations of the identified hyperparameters. Specify the model-building function, the objective metric for optimization (e.g., validation accuracy for PolicyType), the maximum number of trials to perform, and the number of executions for each trial.
3. **Perform Hyperparameter Search**: Initiate the hyperparameter search using the training data and target labels (PolicyType and FraudFound), setting parameters such as the number of epochs and batch size for model training.
4. **Retrieve Optimal Hyperparameters**: Once the search is complete, extract the best hyperparameters found during the tuning process, including the optimal number of units in each LSTM layer, the dropout rates, and the learning rate for analysis.
5. **Build and Train the Final Model**: Using the best hyperparameters obtained, rebuild the LSTM model and train it on the entire training dataset. Implement early stopping if necessary to enhance model training.
6. **Evaluate the Final Model**: After training, evaluate the model's performance using the test dataset. Calculate important performance metrics such as accuracy, mean squared

error, root mean squared error, and AUC-ROC score to assess the model's effectiveness in predicting PolicyType and FraudFound.

7. **Display Evaluation Results**: Present the evaluation results to analyze the impact of hyperparameter tuning on the model's performance, including the calculated metrics for both PolicyType and FraudFound for a comprehensive understanding of its effectiveness.

AUTOENCODERS :

Initial Model Building Steps

Import Libraries: First, import essential libraries such as pandas and numpy for handling data, seaborn for visualizations, and TensorFlow/Keras for building the Autoencoder model. Additionally, use sklearn for data preprocessing and model evaluation.

Load Data: Load your dataset, which contains information for predicting fraud detection and policy type. This dataset may include both categorical and numerical features.

Data Preprocessing: Handle missing values by filling NaNs with the mean or median of the numerical columns. Convert categorical variables using OneHotEncoder and scale the numerical variables using StandardScaler to standardize the input.

Feature Engineering: Define the input features and target variables. Here, FraudFound and PolicyType are used as target variables, converted into numeric representations. Preprocess the categorical and numerical features to create a matrix of features suitable for training.

Split Data: Split the processed dataset into training and testing sets, ensuring a balanced split for effective model evaluation.

Define the Autoencoder Model: Create an autoencoder with an input layer, multiple hidden layers, and an output layer. This neural network will encode and decode data to learn compressed representations of the features.

Train the Autoencoder: Train the autoencoder on the training set with early stopping to avoid overfitting. Early stopping will monitor validation loss, and training will stop if no improvement is observed for a set number of epochs.

Evaluate the Initial Model: After training, the model reconstructs the input data, and the reconstruction error (MSE) is used as a threshold for fraud detection. Evaluate the model’s accuracy and loss before tuning.

Hyperparameter Tuning Steps

Set Up Hyperparameter Tuning: Choose hyperparameters like the number of hidden layers, neurons per layer, activation functions, and learning rate. For tuning, you'll also define the batch size and number of epochs.

K-Fold Cross-Validation: k-fold cross-validation to evaluate the model over different training and validation subsets. This ensures robust evaluation by reducing the variability caused by the train-test split.

Grid Search for Random Forest: After extracting the compressed features from the autoencoder, apply a Random Forest classifier. Perform grid search cross-validation on key hyperparameters (e.g., n_estimators, max_depth) to find the best configuration for the Random Forest classifier.

Evaluate Model After Tuning: Rebuild the best model using the tuned hyperparameters and evaluate it on the test set. Assess the model using metrics such as accuracy, MSE, and AUC-ROC score before and after tuning.

Final Evaluation: Compare the baseline performance to the tuned model's results. Metrics such as accuracy, confusion matrix, and reconstruction error will provide insights into how well the model predicts fraud and policy type after optimization.

CODE :

EXPLORATORY DATA ANALYSIS :

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import mean_squared_error, roc_auc_score, roc_curve, accuracy_score,
confusion_matrix
from sklearn.ensemble import GradientBoostingClassifier
from scipy.stats import randint

file_path = "C:\\Omega\\Semester 5\\Machine Learning\\Project\\final.csv"
data = pd.read_csv(file_path)

print("Dataset Information:")
print(data.info())
print("\nFirst 5 rows of the dataset:")
print(data.head())

print("\nMissing Values:")
print(data.isnull().sum())
data.dropna(inplace=True)
```

```
# 1. Distribution of the target variable
sns.countplot(x='FraudFound', data=data)
plt.title('Distribution of Fraud Found')
plt.xlabel('Fraud Found (0: No, 1: Yes)')
plt.ylabel('Count')
plt.show()

# 2. Distribution of numerical features
numerical_cols = data.select_dtypes(include=[np.number]).columns
data[numerical_cols].hist(bins=15, figsize=(15, 10))
plt.suptitle('Distribution of Numerical Features')
plt.show()

# 3. Outlier Detection using box plots
num_cols = len(numerical_cols)
cols_per_row = 4
rows = (num_cols // cols_per_row) + (num_cols % cols_per_row > 0)

plt.figure(figsize=(20, 5 * rows))
for i, col in enumerate(numerical_cols):
    plt.subplot(rows, cols_per_row, i + 1)
    sns.boxplot(x=data[col])
    plt.title(f'Box Plot of {col}')
    plt.xlim(data[col].min() - 1, data[col].max() + 1)

plt.subplots_adjust(hspace=0.95, top=0.933)
plt.show()

# 4. Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:")
print(cm)

# Visualizing the Confusion Matrix
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='g', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

GRADIENT BOOSTED NEURAL NETWORK :

Initial Model Building :

```
def create_model():
    model = Sequential()
    model.add(Dense(32, activation='relu', input_dim=X_train.shape[1]))  # Input layer
    model.add(Dense(16, activation='relu'))  # Hidden layer
    model.add(Dense(1, activation='sigmoid'))  # Output layer
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

def gradient_boosted_nn(X_train, y_train, X_test, n_estimators=5):
    n_samples = len(y_train)
    y_pred = np.zeros(n_samples)
    models = []
    for _ in range(n_estimators):
        residuals = y_train - y_pred
        model = create_model()
        model.fit(X_train, residuals, epochs=10, batch_size=32, verbose=0)
        y_pred += model.predict(X_train).flatten()  # Flatten to match y_train shape
        models.append(model)
    return models, y_pred
models, y_train_pred = gradient_boosted_nn(X_train, y_train, X_test)
```

Parameter Tuning :

```
def create_model(neurons_1=32, neurons_2=16):
    model = Sequential()
    model.add(Input(shape=(X_train.shape[1],)))  # Input layer using Input
    model.add(Dense(neurons_1, activation='relu'))  # Hidden layer
    model.add(Dense(neurons_2, activation='relu'))  # Hidden layer
    model.add(Dense(1, activation='sigmoid'))  # Output layer
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

# Function to perform hyperparameter tuning
def hyperparameter_tuning(X_train, y_train):
    param_dist = {
        'neurons_1': [16, 32, 64],
        'neurons_2': [8, 16, 32],
        'epochs': [10, 20],
        'batch_size': [16, 32]
    }
  # Random search over specified parameter values
    for neurons_1 in param_dist['neurons_1']:
```

```
        for neurons_2 in param_dist['neurons_2']:
            for epochs in param_dist['epochs']:
                for batch_size in param_dist['batch_size']:
                    # Create and train model
                    model = create_model(neurons_1=neurons_1, neurons_2=neurons_2)
                    model.fit(X_train, y_train, epochs=epochs, batch_size=batch_size, verbose=0)
                    # Evaluate model
                    y_train_pred = model.predict(X_train).flatten()
                    y_train_pred_binary = (y_train_pred > 0.5).astype(int)
                    accuracy = accuracy_score(y_train, y_train_pred_binary)
                    # Check if this is the best model
                    if accuracy > best_accuracy:
                        best_accuracy = accuracy
                        best_params = {
                            'neurons_1': neurons_1,
                            'neurons_2': neurons_2,
                            'epochs': epochs,
                            'batch_size': batch_size
                        }
    return best_params

# Implement k-fold cross-validation to prevent overfitting
def k_fold_validation(X, y, n_splits=5):
    kfold = KFold(n_splits=n_splits, shuffle=True, random_state=42)
    fold_no = 1
    results = []
    for train_idx, val_idx in kfold.split(X):
        X_train_fold, X_val_fold = X[train_idx], X[val_idx]
        y_train_fold, y_val_fold = y[train_idx], y[val_idx]
```

FEED FORWARD NEURAL NETWORK :

Initial Model Building :

```
# Define a function to create the neural network
def create_model():
    model = Sequential()
    model.add(Dense(32, activation='relu', input_dim=X_train.shape[1]))  # Input layer
    model.add(Dense(16, activation='relu'))  # Hidden layer
    model.add(Dense(1, activation='sigmoid'))  # Output layer
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model
```

Parameter Tuning :

```
# Define the model building function with hyperparameters
def build_model(hp):
    model = Sequential()
    # Choose number of hidden layers
    num_hidden_layers = hp.Int('num_hidden_layers', min_value=1, max_value=3)
    # Add input layer
    model.add(Dense(units=hp.Int('neurons_input_layer', min_value=16, max_value=64,
step=16),
                    activation=hp.Choice('activation_input_layer', values=['relu', 'tanh']),
                    input_dim=X_train.shape[1]))
    # Add hidden layers
    for _ in range(num_hidden_layers - 1):
        model.add(Dense(units=hp.Int('neurons_hidden_layer', min_value=16, max_value=64,
step=16),
                        activation=hp.Choice('activation_hidden_layer', values=['relu', 'tanh'])))

    # Add output layer
    model.add(Dense(1, activation='sigmoid'))  # Output layer
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

# Set up the tuner
tuner = kt.tuners.RandomSearch(
    build_model,
    objective='val_accuracy',
    max_trials=10,
    executions_per_trial=3,
    directory='my_dir',
    project_name='fraud_detection'
)
```

LSTM – (LONG SHORT TERM MEMORY)

Initial Model Building :

```
def build_model(hp):
    model = Sequential()

    # First LSTM layer with hyperparameter tuning for units
    model.add(LSTM(
        units=hp.Int('units', min_value=32, max_value=128, step=16),
        input_shape=(X_train_reshaped.shape[1], X_train_reshaped.shape[2]),
        return_sequences=True
```

```
    ))
    model.add(Dropout(hp.Float('dropout', min_value=0.2, max_value=0.5, step=0.1)))
    # Second LSTM layer
    model.add(LSTM(
        units=hp.Int('units_2', min_value=32, max_value=128, step=16),
        return_sequences=False
    ))
    model.add(Dropout(hp.Float('dropout_2', min_value=0.2, max_value=0.5, step=0.1)))
    # Output layer
    model.add(Dense(1, activation='sigmoid'))
    # Compile the model with a tuned learning rate
    model.compile(
        optimizer=Adam(learning_rate=hp.Float('learning_rate', min_value=1e-4, max_value=1e-2,
sampling='log')),
        loss='binary_crossentropy',
        metrics=['accuracy']
    )

    return model
```

Parameter Tuning :

```
# Set up Keras Tuner Random Search for hyperparameter tuning
tuner = RandomSearch(
    build_model,
    objective='val_accuracy',
    max_trials=10,  # Number of hyperparameter combinations to try
    executions_per_trial=1,  # Number of models to train per trial
    directory='tuner_results',
    project_name='lstm_fraud_detection'
)
# Perform the search for the best hyperparameters
tuner.search(X_train_reshaped, y_train, epochs=10, batch_size=32, validation_split=0.2)
# Get the optimal hyperparameters
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]
```

AUTOENCODERS

Initial Model Building :

```
default_model = create_autoencoder(default_hidden_layers, default_neurons, default_activation)
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)
default_model.fit(X_train, X_train,
                  epochs=default_epochs,
                  batch_size=default_batch_size,
```

```
            validation_split=0.2,
            callbacks=[early_stopping],
            verbose=0)
```

Parameter Tuning :

```
best_model = None
best_params = {}
best_loss = float('inf')
tuning_count = 0  # Counter for tuning iterations

# Example hyperparameter values
hidden_layers_list = [1, 2]
neurons_list = [8, 16, 32]
activation_functions = ['relu', 'tanh']
epochs_list = [5, 10]
batch_sizes = [16, 32]

for hidden_layers in hidden_layers_list:
    for neurons in neurons_list:
        for activation in activation_functions:
            for epoch in epochs_list:
                for batch_size in batch_sizes:
                    if tuning_count < 10:

                        autoencoder = create_autoencoder(hidden_layers, neurons, activation)
                        early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)
                        history = autoencoder.fit(X_train, X_train,
                                                  epochs=epoch,
                                                  batch_size=batch_size,
                                                  validation_split=0.2,
                                                  callbacks=[early_stopping],
                                                  verbose=0)

                        # Evaluate the model on the test set
                        loss = autoencoder.evaluate(X_test, X_test, verbose=0)
                        print(f'Hidden Layers: {hidden_layers}, Neurons: {neurons}, Activation:
{activation}, '
                              f'Epochs: {epoch}, Batch Size: {batch_size}, Loss: {loss}')

                        # Update best model if current loss is lower
                        if loss < best_loss:
                            best_loss = loss
```

```
                best_model = autoencoder
                best_params = {
                    'hidden_layers': hidden_layers,
                    'neurons': neurons,
                    'activation': activation,
                    'epochs': epoch,
                    'batch_size': batch_size
                }

                tuning_count += 1  # Increment the counter
            else:
                break
```

PREDICTION :
Fraud :

```
# Fraud Detection page
if st.session_state.page == 'fraud_detection':
    st.markdown('<h2 style="color: #FF8C00;">Fraud Detection</h2>', unsafe_allow_html=True)

    # Collect user input
    fraud_input = get_fraud_input()

    # Button to trigger prediction
    if st.button("Detect Fraud"):
        # Scale the input
        fraud_scaled_input = fraud_scaler.transform(fraud_input[fraud_features])

        # Reshape input for the LSTM model
        fraud_input_reshaped = fraud_scaled_input.reshape(1, 1, len(fraud_features))

        # Predict using the trained LSTM model
        fraud_prediction = fraud_model.predict(fraud_input_reshaped)
        st.markdown(f"<p class='prediction-result'>Raw Prediction Probability of Fraud:
<strong>{fraud_prediction[0][0]:.4f}</strong></p>", unsafe_allow_html=True)

        # Custom decision-making based on input values (optional)
        if fraud_input['ClaimAmount'].values[0] > 25000 and
fraud_input['PastNumberOfClaims'].values[0] > 5:
            decision = "Fraud"
        else:
            decision = "Not Fraud"
```

Policy Type :

```
# Insurance Policy Prediction page
if st.session_state.page == 'insurance_policy':
    st.markdown('<h2 style="color:#FF6347;">Insurance Policy Prediction</h2>',
unsafe_allow_html=True)

    # Collect user input
    policy_input = get_policy_input()

    # Button to trigger prediction
    if st.button("Predict Policy"):
        # Scale the input
        policy_input_scaled = policy_scaler.transform(policy_input)

        # Predict using the trained model
        policy_prediction_proba = policy_model.predict(policy_input_scaled)
        predicted_class = np.argmax(policy_prediction_proba)
        predicted_label = label_encoder.inverse_transform([predicted_class])[0]

        st.markdown(f"<p class='prediction-result'>Predicted Policy Type:
<strong>{predicted_label}</strong></p>", unsafe_allow_html=True)
```

OUTPUT :

Exploratory Data Analysis :

Dataset Information:

RangeIndex: 150000 entries, 0 to 149999

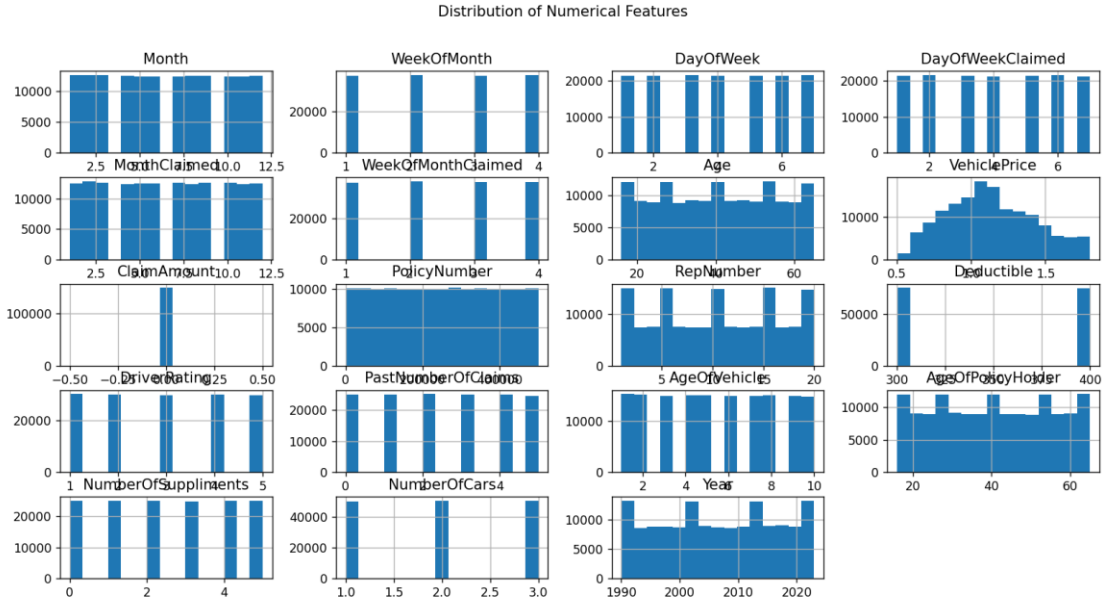
Data columns (total 34 columns):

#	Column	Non-Null Count	Dtype
0	Month	150000 non-null	int64
1	WeekOfMonth	150000 non-null	int64
2	DayOfWeek	150000 non-null	int64
3	Make	150000 non-null	object
4	AccidentArea	150000 non-null	object
5	DayOfWeekClaimed	150000 non-null	int64
6	MonthClaimed	150000 non-null	int64
7	WeekOfMonthClaimed	150000 non-null	int64
8	Sex	150000 non-null	object
9	MaritalStatus	150000 non-null	object
10	Age	150000 non-null	int64

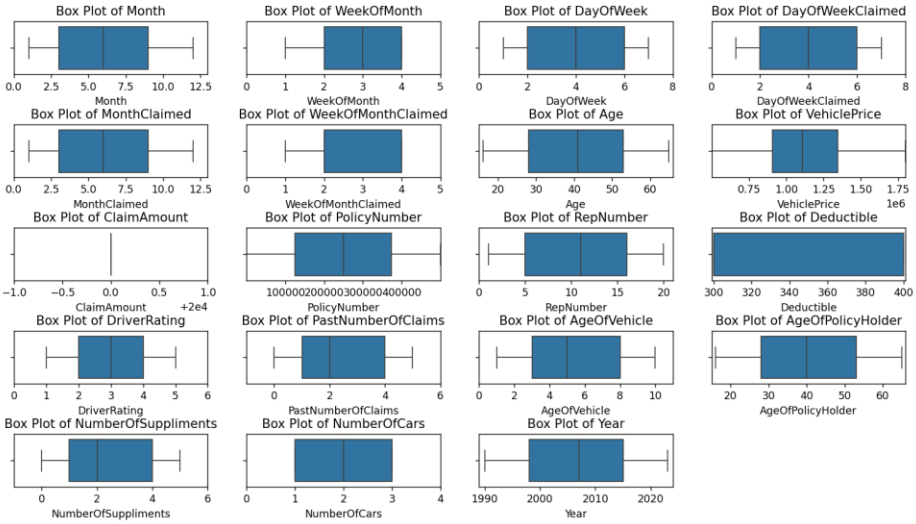
```
 11  Fault                 150000 non-null  object
 12  PolicyType            150000 non-null  object
 13  VehicleCategory       150000 non-null  object
 14  VehiclePrice          150000 non-null  float64
 15  ClaimAmount           150000 non-null  float64
 16  PolicyNumber          150000 non-null  int64
 17  RepNumber             150000 non-null  int64
 18  Deductible            150000 non-null  int64
 19  DriverRating          150000 non-null  int64
 20  Days:Policy-Accident  150000 non-null  object
 21  Days:Policy-Claim     150000 non-null  object
 22  PastNumberOfClaims    150000 non-null  int64
 23  AgeOfVehicle          150000 non-null  int64
 24  AgeOfPolicyHolder     150000 non-null  int64
 25  PoliceReportFiled     150000 non-null  object
 26  WitnessPresent        150000 non-null  object
 27  AgentType             150000 non-null  object
 28  NumberOfSuppliments   150000 non-null  int64
 29  AddressChange-Claim   150000 non-null  object
 30  NumberOfCars          150000 non-null  int64
 31  Year                  150000 non-null  int64
 32  BasePolicy            150000 non-null  object
 33  FraudFound            150000 non-null  object
dtypes: float64(2), int64(17), object(15)
memory usage: 38.9+ MB
```

1. Distribution of the target variable

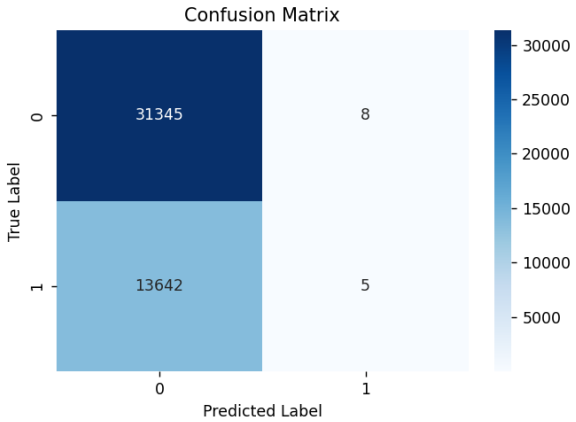
2. Distribution of numerical features



3. Outlier Detection using box plots



4. Confusion Matrix



Gradient Boosted Neural Network :

1.Fraud Detection :

- **Initial model building :**

Gradient Boosted Neural Networks - Accuracy: 0.6966, MSE: 0.3034, MAE: 0.3034, ROC AUC: 0.5035

- **Hyper parameter tuning :**

Final Model with Best Parameters - Accuracy: 0.6905, MSE: 0.3095, MAE: 0.3095, ROC AUC: 0.4967
Best Parameters: {'neurons_1': 64, 'neurons_2': 32, 'epochs': 20, 'batch_size': 16}
Final Model with Best Parameters - Accuracy: 0.6879, MSE: 0.3121, MAE: 0.3121, ROC AUC: 0.5048
Fold 1 - Accuracy: 0.6962
Fold 2 - Accuracy: 0.7003
Fold 3 - Accuracy: 0.6995
Fold 4 - Accuracy: 0.7009
Fold 5 - Accuracy: 0.6988
Average accuracy after k-fold cross-validation: 0.6992
Final Model with Best Parameters - Accuracy: 0.7002, MSE: 0.2998, MAE: 0.2998, ROC AUC: 0.5052

2.Policy type prediction :

- **Initial model building :**

Gradient Boosted Neural Networks - Accuracy for Policy Type: 0.3346
MSE: 1.3564, MAE: 0.8957, ROC AUC: 0.5001

- **Hyper parameter tuning :**

Best Parameters: {'neurons_1': 128, 'neurons_2': 64, 'dropout_rate': 0.2, 'epochs': 20, 'batch_size': 64}
Accuracy: 0.3340, MSE: 1.4310, MAE: 0.9210, ROC AUC: 0.5005

Feed forward neural network :

1.Fraud Detection :

- **Initial model building :**

EPOCHS	ACCURACY	MSE	RMSE	MAE	ROC - AUC
50	0.6931	0.3069	0.5540	0.3069	0.5025
20	0.6958	0.3042	0.5516	0.3042	0.5063
10	0.6993	0.3007	0.5484	0.3007	0.5001

- **Hyper parameter tuning :**

TRIAL 1	TRIAL 2	TRIAL 3	TRIAL 4	TRIAL 5	TRIAL 6	TRIAL 7	TRIAL 8	TRIAL 9	TRIAL 10
0.70322	**0.70323**	**0.70322**	**0.70322**	**0.70322**	**0.70323**	**0.70320**	**0.70320**	**0.70323**	**0.703208**

Best val_accuracy So Far: 0.7032361030578613
Total elapsed time: 00h 52m 02s

Best Accuracy: 0.7002
MSE: 0.2998
RMSE: 0.5475
MAE: 0.2998
ROC AUC: 0.5037

2.Policy type prediction :

- **Initial model building :**

Feedforward Neural Networks - Accuracy for Policy Type: 0.3351
MSE: 1.3589, MAE: 0.8963, ROC AUC: 0.4995

- **Hyper parameter tuning :**

Best Hyperparameters: {'optimizer': 'adam', 'model_neurons_2': 64, 'modelneurons_1': 128, 'model_dropout_rate': 0.2, 'epochs': 30, 'batch_size': 128}
Final Model - Accuracy: 0.3347
MSE: 1.2829
MAE: 0.8711
ROC AUC: 0.4994

LSTM – Long Short Term Memory :

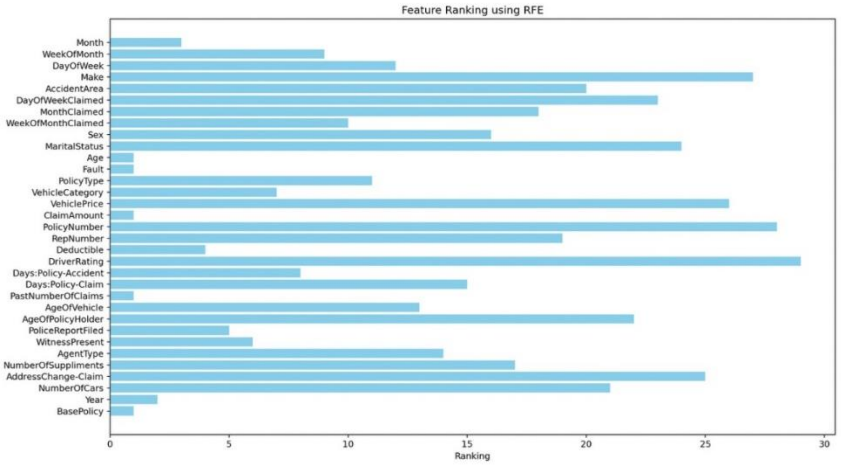
1.Fraud Detection :

- **Initial model building :**

Before Hypertuning:
MSE: 0.1075
RMSE: 0.3279
AUC-ROC: 0.6056
Accuracy: 0.8733

- **Hyper parameter tuning :**

Feature Selection :



MSE: 0.0796
RMSE: 0.2821
AUC-ROC: 0.6101
Accuracy: 0.9150

2.Policy type prediction :

- **Initial model building :**

Accuracy: 0.3345
RMSE: 1.1594826432508596
MSE: 1.3444
AUC-ROC: 0.49916387209903984

- **Hyper parameter tuning :**

Accuracy: 0.3307
RMSE: 1.2427389106324787
MSE: 1.5444
AUC-ROC: 0.5019477077758844

Autoencoders :

1.Fraud Detection :

- **Initial model building :**

MSE: 0.3215
RMSE: 0.5670
AUC-ROC Score: 0.4963
Accuracy: 0.6785

- **Hyper parameter tuning :**

MSE: 0.3517
RMSE: 0.6214
AUC-ROC Score: 0.3524
Accuracy: 0.6945

2.Policy type prediction :

- **Initial model building :**

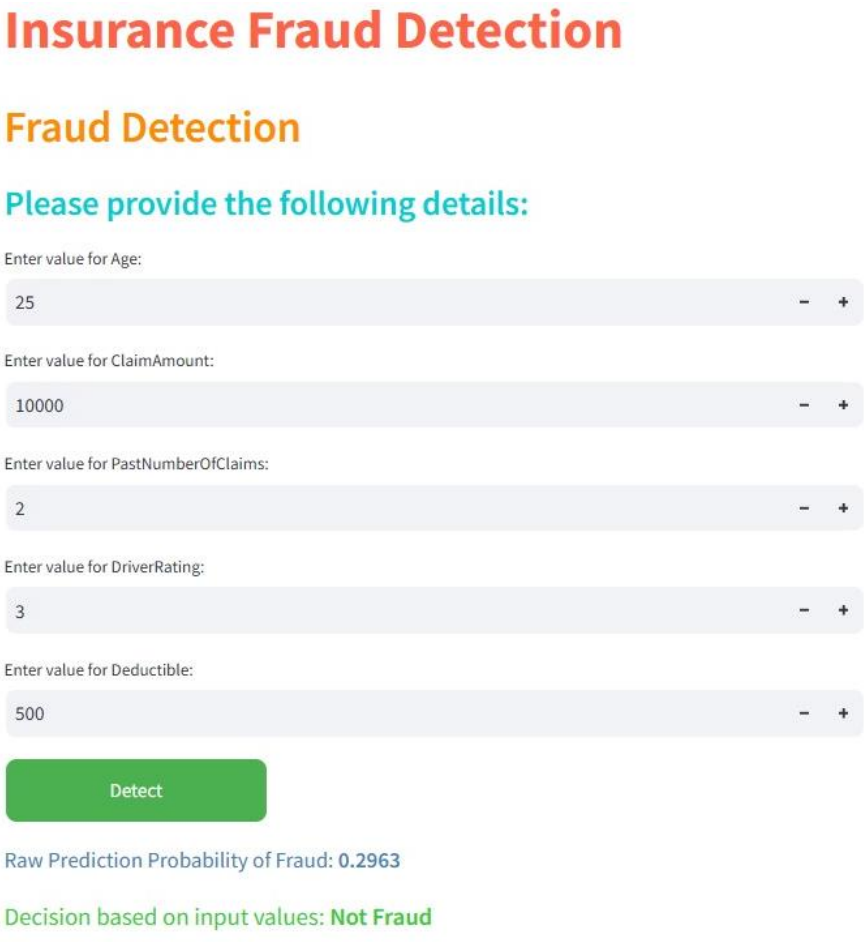
MSE: 1.6432
RMSE: 1.6743
AUC-ROC Score: 0.5002
Accuracy: 0.3331

- **Hyper parameter tuning :**

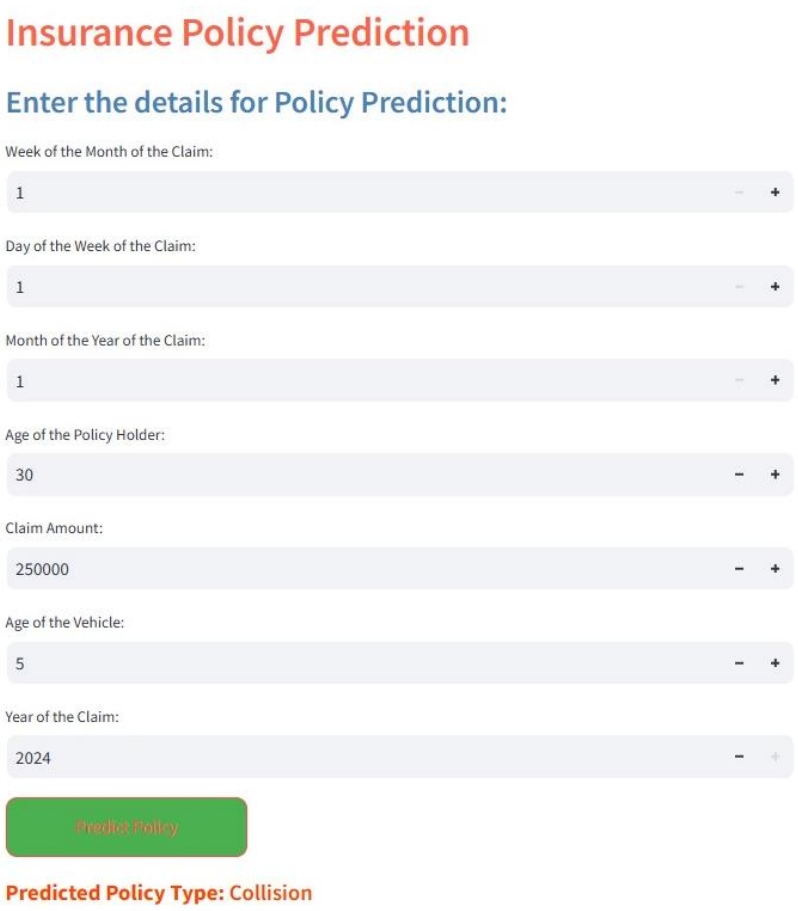
MSE: 1.6637
RMSE: 1.6872
AUC-ROC Score: 0.5000
Accuracy: 0.3331

Prediction :

Fraud Detection :



Insurance Policy Prediction :



BUSINESS INSIGHT :

The insurance website is a valuable tool for both regular customers and insurance agents, helping them make informed decisions with ease. It allows common people to predict what kind of insurance policy suits them best, and it helps insurance agents detect if a claim might be fraudulent. This website not only makes the process simpler for users but also brings significant benefits to the insurance company and society as a whole.

Benefiting Common People with Insurance Policy Prediction

For regular customers, the website provides a user-friendly tool to help them understand and choose the most suitable insurance policy. By entering details such as vehicle information and past accident history, the website uses smart technology to recommend the best insurance plan for their needs. Here's how it benefits common people:

- **Get the Right Coverage**: Often, people end up choosing insurance policies that might not be perfect for their needs. Some pay for coverage they don't need, while others might miss out on important protection. This website fixes that problem by giving personalized suggestions based on the user's specific information. This way, users get the right amount of coverage without paying too much or too little.

Benefiting Insurance Agents with Fraud Detection

For insurance agents, the website offers a powerful tool to help them detect potentially fraudulent claims. This is crucial because fake claims cost insurance companies a lot of money. By using this tool, agents can quickly and easily identify suspicious claims, which helps them focus on cases that need more attention. Here's how the website benefits agents:

- **Saving Time**: Normally, insurance agents have to manually check every claim to see if it's genuine or not, which can take a lot of time. With the website, they just input the claim details, and the system uses advanced models like **Autoencoders** and **Gradient Boosted Neural Networks (GBNN)** to predict whether the claim is likely to be fraudulent. This allows agents to focus their time on the claims that are most suspicious, speeding up the whole process.
- **Improved Accuracy**: The predictive models used by the website are designed to spot patterns that indicate fraud. These patterns might not be obvious to humans, but the models can detect them quickly. This means that agents can rely on the website to give them accurate predictions, helping them make better decisions about which claims need more investigation. As a result, fewer fraudulent claims go unnoticed, and genuine claims can be processed more quickly.

Benefiting the Insurance Company

From a business perspective, the website provides several advantages to the insurance company:

- **Increased Efficiency**: By automating the process of policy prediction and fraud detection, the company can handle more customer requests and claims without needing to hire more staff. This saves both time and money, as the system can work much faster than humans. It also means the company can serve more customers in less time, which improves customer satisfaction.
- **Preventing Fraud-Related Losses**: Fraudulent claims can cost the insurance company a lot of money. By using the website's fraud detection tool, the company can avoid paying out on fake claims. This reduces the company's losses and allows them to focus their resources on providing better services to genuine customers. In the long run, this also helps the company keep its premiums competitive, as they won't need to raise prices to cover fraud-related losses.
- **Using Advanced Technology for Better Decision-Making**: The website uses sophisticated models like **LSTM (Long Short-Term Memory)**, which can detect patterns in data over time. For example, it might spot trends in when or where claims are filed, helping the company forecast potential future risks. This kind of insight allows the company to make better decisions about pricing policies, managing claims, and allocating resources.

GIT REPOSITORY LINK :

https://github.com/Omega-Semmalai/Insurance-Policy-and-fraud-prediction