**Chapter 1: Introduction**

**1.1 Problem Statement**

The rise of social media platforms has brought about an increase in fake accounts, which are used for malicious purposes such as spreading misinformation, conducting scams, and manipulating trends. Detecting these fake accounts is critical for maintaining trust and security online. This study implements a machine learning approach, using the Random Forest model, to detect and classify fake social media accounts. The model will leverage user profile features such as the presence of profile pictures, username characteristics, and the number of posts, followers, and follows to predict account authenticity.

**1.2 Objective of the Study**

The objective of this study is to develop a machine learning model to identify fake social media accounts. Specifically, the study focuses on:

* Pre-processing features from user profiles, including profile pictures, username length, and user activity metrics (posts, followers, follows).
* Implementing a Random Forest model to classify accounts as either fake or real.
* Evaluating model performance using accuracy, precision, recall, and F1-score.

**1.3 Scope of the Study**

This study focuses on detecting fake social media accounts using a dataset containing features like profile pictures, username length, and user activity metrics. The model is trained using the Random Forest classifier, and performance is evaluated using standard classification metrics.

**Chapter 2: Methodology**

**2.1 Overview**

The methodology involves data pre-processing, model development, and performance evaluation. The approach includes the following steps:

1. **Data Collection and Pre-processing**: Gathering and cleaning the dataset, handling missing values, and extracting relevant features from user profiles.
2. **Model Development**: Training the Random Forest classifier using the processed data.
3. **Evaluation**: Assessing the model’s performance using metrics such as accuracy, precision, recall, and F1-score.

**2.2 Random Forest Model**

The Random Forest model is an ensemble learning method that combines multiple decision trees to improve classification accuracy. It works by training several decision trees on random subsets of data and aggregating their results for better generalization.

**Chapter 3: Data Collection and Preparation**

**3.1 Dataset Description**

The dataset consists of social media user profiles, each with the following features:

* **profile\_pic**: Presence of a profile picture (binary: 1 for yes, 0 for no).
* **ratio\_numlen\_username**: Ratio of numeric characters to total username length.
* **len\_fullname**: Length of the user’s full name.
* **ratio\_numlen\_fullname**: Ratio of numeric characters to total full name length.
* **sim\_name\_username**: Whether the user’s name matches their username (binary: 1 for match, 0 for no match).
* **len\_desc**: Length of the user’s account description.
* **extern\_url**: Whether the account description includes an external URL (binary: 1 for yes, 0 for no).
* **private**: Whether the user’s posts are visible only to followers (binary: 1 for private, 0 for public).
* **num\_posts**: Number of posts by the user.
* **num\_followers**: Number of followers of the user.
* **num\_following**: Number of accounts the user is following.
* **fake**: Whether the account is real (0) or fake (1).

**3.2 Data Pre-processing**

* **Handling Missing Values**: Any missing data points are addressed by imputation or removal.
* **Feature Encoding**: Categorical variables, such as the presence of a profile picture, are encoded into numerical formats.
* **Feature Scaling**: Numerical features are scaled to ensure consistent input to the model.
* **Data Splitting**: The dataset is split into training and testing sets to evaluate the model's performance.

**Chapter 4: Model Design**

**4.1 Model Selection**

A **Random Forest classifier** is chosen due to its robustness, ability to handle large datasets, and effectiveness in managing overfitting. It works by constructing multiple decision trees based on random subsets of the data and averaging their predictions.

**4.2 Model Training**

* **Training Data**: The training data is used to build multiple decision trees.
* **Hyper parameter Tuning**: Grid search is performed to tune hyper parameters such as the number of trees, maximum depth, and minimum samples split.
* **Model Evaluation**: The trained model is evaluated using testing data and various classification metrics.

**Chapter 5: Result Analysis**

**5.1 Performance Metrics**

The model's performance is evaluated using:

* **Accuracy**: The percentage of correctly classified instances.
* **Precision**: The ratio of true positive predictions to the total number of positive predictions.
* **Recall**: The ratio of true positive predictions to the total number of actual positives.
* **F1-Score**: The harmonic mean of precision and recall.

**Chapter 6: Confusion Matrix**

**6.1 Confusion Matrix Interpretation**

The confusion matrix provides a detailed summary of the model’s performance, showing the number of:

* True Positives (TP): Correctly classified fake accounts.
* True Negatives (TN): Correctly classified real accounts.
* False Positives (FP): Real accounts incorrectly classified as fake.
* False Negatives (FN): Fake accounts incorrectly classified as real.

The matrix allows for a deeper understanding of where the model is making errors and provides a basis for improving the model through further tuning or data adjustments.

**Chapter 7: Classification Report**

**7.1 Classification Report Overview**

The classification report summarizes the precision, recall, and F1-score for each class (fake and real accounts). This report is critical for understanding the trade-offs between precision and recall and identifying areas where the model can be improved. The report is based on the confusion matrix and is a key tool in evaluating the model’s effectiveness.

**Chapter 8: Key Insights**

**8.1 Insights from Feature Importance**

Feature importance analysis helps identify which attributes of user profiles are most influential in predicting fake accounts. Features such as the number of posts, followers, and follows may provide valuable insights into the behaviour of fake accounts.

**8.2 Model Limitations and Improvements**

* **Data Quality**: The accuracy of the model depends heavily on the quality and representativeness of the dataset.
* **Model Complexity**: While the Random Forest model performs well, exploring more complex models like neural networks could further improve accuracy.