UNIVERSITY OF LONDON

INTERNATIONAL PROGRAMMES

BSc Computer Science and Related Subjects

CM3070 PROJECT
FINAL PROJECT REPORT

<Credit Card Fraud Detection Using Neural Networks>

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CHAPTER 1: INTRODUCTION

This chapter serves as an introduction to the final year project report. It provides an overview of the project template, concept, motivation, aims, deliverables, and justification for objectives.

1.1. Project Template

My final year project uses the project template from the module CM3015 Machine Learning and Neural Networks, "Deep Learning on a public dataset".

1.2. Project Concept and Motivation

Making payments is now easier than ever due to the rapid advancement of technology in the financial industry. However, it has created new opportunities for illegal activity, such as credit card fraud. Credit card fraud occurs when unauthorised users gain access to an individual's credit card information. They may then use the information to make purchases, fund other transactions or open new accounts (Wikipedia, 2024). This may have serious implications for both consumers and financial institutions. For example, consumers may suffer major financial losses and financial institutions may lose trust and goodwill. Furthermore, scammers are always coming up with new and inventive ways to take advantage of loopholes in banking systems. To reduce such losses and improve the security of financial transactions, there is hence, a need to have a strong fraud detection system. To meet this demand, my final year project aims to develop a high-performing neural network model that can accurately identify credit card fraud transactions.

1.3. Project Aims

The primary aim of my project is to design and implement a high-performing neural network model that can detect fraud transactions with high accuracy, precision, recall, and F1-score. The model should also demonstrate low training and validation losses. Table 1 below elaborates on these aims.

Aim	Explanation
High accuracy	The model correctly identifies the majority of transactions (both fraud and non-fraud).
High precision	When the model predicts a transaction as fraudulent, it is likely to be correct. This minimises false positives.
High recall	The model identifies most fraud transactions, minimising false negatives.
High F1-score	The model maintains both low false positives and false negatives.
Low training loss	The model accurately fits the training data.
Low validation loss	The model generalises well to unseen data with minimal overfitting.

Table 1: Summary of project aims and explanations

Another aim of my project is to address the issue of imbalanced data in the chosen dataset. Since fraud transactions usually only represent a small portion of all transactions, the model's performance may be negatively impacted by a class imbalance issue. Hence, my project will apply resampling techniques to tackle this. These techniques help balance the representation of fraud and non-fraud transactions in the training data, ensuring the model is trained effectively.

1.4. Project Deliverables

The deliverables of my project includes a final report explaining the following (Table 2):

Deliverable	**Explanation**
Exploratory data analysis	An overview of the dataset, including its characteristics and the distribution of fraud and non-fraud transactions.
Comprehensive data processing	Preprocessing steps applied to the dataset, including handling missing data, feature scaling, and resampling techniques.
Neural network architecture design	The design and implementation of an effective neural network for fraud detection. This includes descriptions of its architecture, such as the number of layers, types of layers, and activation functions.
Model training and hyperparameter tuning	Model training and performance optimisation. This includes descriptions of the training process, chosen optimiser, loss function, batch size, number of epochs, and hyperparameter tuning techniques.
Model testing and evaluation	Assessment of the model's performance using evaluation metrics such as accuracy, precision, recall, F1-score, and training and validation loss curves.
Visualisations	Visualisations such as dataset distribution, training and validation loss curves, and confusion matrix heatmaps.

Table 2: Summary of project deliverables and explanations

1.5. Justification of Objectives

Each objective is selected to ensure my project meets its aims of developing a high-performing neural network model that can accurately identify credit card fraud transactions. Table 3 below summarises its justification.

Justification	Explanation
Exploratory data analysis Data processing	This is necessary for understanding the data and preparing it for the model training process.
Neural network architecture design Model training and hyperparameter tuning	This is necessary to determine the best model that is fit for the fraud detection task.
Model testing and evaluation	This is necessary to ensure that the model performs well on both seen and unseen data.
Visualisations	This is necessary to provide visual insight and helps with interpretation of results.

Table 3: Summary of objective justification and explanations

Number of words for Chapter 1: 393

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

This chapter serves as a literature review to analyse various methods for detecting credit card fraud. It discusses both traditional machine learning algorithms and modern deep learning models. It also discusses resampling techniques for handling class imbalance.

Traditional methods like logistic regression, random forest, and k-nearest neighbours were used in earlier days for their simplicity and interpretability. However, with the increasing complexity of fraud detection and the availability of powerful computing resources, deep learning models have become more popular. Among them are feedforward neural networks (FNN), convolutional neural networks (CNN) and recurrent neural networks (RNN). Resampling refers to oversampling, undersampling or combining different sampling techniques.

2.2. Traditional Credit Card Fraud Detection Algorithms

2.2.1. Overview of Traditional Algorithms

Traditional algorithms serve as the foundation for more complex models and provide a benchmark for evaluating newer techniques. These include logistic regression, random forest and k-nearest neighbours.

2.2.2. Logistic Regression

Logistic regression is a supervised machine learning algorithm used for binary classification problems. It uses the sigmoid function to transform a linear combination of input features into a probability value between 0 and 1. The textbook "Pattern Recognition and Machine Learning" discusses logistic regression as a fundamental tool for probabilistic classification tasks (Bishop, 2006).

In a Kaggle project by Jimy, logistic regression was applied to predict the probability of a transaction being fraudulent based on features such as transaction amount and time. The project also demonstrates that this algorithm is easy to implement, by just using LogisticRegression() from the sklearn Python library. Furthermore, the logistic regression model yielded impressive performance metrics, including high accuracy, recall, and F1-score (Jimy, 2024). These results show the algorithm's capability to effectively identify fraud transactions while balancing false positives and false negatives. However, logistic regression assumes a linear relationship between features, which may not always be true.

2.2.3. Random Forest

Random forest, or random decision forest, is an ensemble algorithm for classification problems. It builds many decision trees during training and combines their outputs to make the final prediction. In the context of credit card fraud detection, research has illustrated the effectiveness of random forests in capturing intricate patterns within transaction data, thereby enhancing detection performance (Breiman, 2001).

In a Kaggle project by Preda, the random forest algorithm was applied to detect credit card fraud and yielded an impressive ROC-AUC score. This result highlights the algorithm’s capability to effectively capture complex relationships between features and detect non-linear patterns in credit card transactions (Preda, 2021). Random forest algorithms mitigate overfitting by aggregating predictions from multiple decision trees, each trained on different subsets of data and features. This enhances the model’s performance on unseen data, making it a robust choice for fraud detection tasks.

2.2.4. K-Nearest Neighbours (KNN)

KNN is a supervised machine learning algorithm used for classification problems. It finds the k-nearest data points to a given input and assigns the most common class as the prediction. The algorithm's simplicity and effectiveness in classifying credit card transactions based on similarities have been demonstrated in the textbook "Pattern Recognition and Machine Learning" (Bishop, 2006).

In a Kaggle project by Bachmann, KNN was applied to classify credit card transactions as fraudulent or legitimate based on features such as transaction amount and time. The project also demonstrates that this algorithm is easy to implement, by just using KNeighborsClassifier() from the sklearn Python library. Furthermore, the KNN model yielded impressive performance metrics, including high training accuracy and high cross validation (Bachmann, 2019). These results show the algorithm’s capability to effectively classify transactions based on similarity to known fraud cases. However, KNN’s effectiveness heavily depends on the choice of distance metric and the k value. It may also struggle with large datasets due to the computational resources required to calculate distances between data points.

2.3. Deep Learning Models for Fraud Detection

2.3.1. Overview of Deep Learning Models

Deep learning models represent a significant advancement in machine learning, categorised by their ability to automatically learn hierarchical representations of data through the use of multiple layers of neural networks. These include feedforward neural networks, recurrent neural networks, and convolutional neural networks.

2.3.2. Feedforward Neural Networks (FNN)

FNNs are one of the most fundamental types of artificial neural networks. They are often used as a baseline in machine learning tasks, including credit card fraud detection. In an FNN, data moves in one direction (from input nodes, through hidden layers, to output nodes) without looping back. This structure enables the network to model complex, non-linear relationships between features by applying a series of transformations and activations (Sazli, 2006). (Carcillo et al., 2021) demonstrated the effectiveness of FNNs by incorporating it as part of a broader framework for real-time fraud detection in their SCARFF (Scalable Real-time Fraud Finder) system. Their findings illustrate that the framework is scalable, efficient, and accurate over a large stream of transactions.

2.3.3. Recurrent Neural Networks (RNN)

RNNs are a specialised class of artificial neural networks designed to handle sequential data and temporal dependencies. In contrast to FNNs, RNNs use feedback loops to allow information to persist across layers, enabling them to model dynamic behaviours over time (Sazli, 2006). This makes RNNs suitable for analysing sequences of credit card transactions, where patterns may evolve over multiple transactions. Carcillo et al. (2021) also incorporated RNNs in their SCARFF framework for real-time fraud detection, demonstrating the effectiveness of RNNs to capture temporal patterns that signal fraudulent activities. Their findings illustrate RNNs’ capability to process continuous streams of transaction data efficiently, thereby enhancing detection accuracy.

2.3.4. Convolutional Neural Networks (CNN)

CNNs are another specialised class of artificial neural networks designed to process data with a grid-like topology, such as images. Their architecture includes convolutional layers, pooling layers, and fully connected layers, making them suited for various data types. These data types include time-series and tabular data, which are common in credit card fraud detection (Goodfellow, Bengio, and Courville, 2016). Research by (Jurgovsky et al., 2018) demonstrated the effectiveness of CNNs in detecting fraudulent transactions by transforming the sequential data of transactions into a format suitable for convolutional operations. Their findings illustrate that CNNs could significantly enhance the detection performance by identifying intricate patterns in transaction sequences. Furthermore, CNNs have been integrated into various real-time fraud detection systems, showing robust performance in handling large-scale streaming data (Yeh & Lien, 2016).

2.4. Resampling Techniques

2.4.1. Overview of resampling techniques

Resampling techniques are essential in machine learning to address class imbalance (one of the project's aims). Class imbalance occurs when one class (in this case, fraud transactions) is significantly underrepresented compared to the other (non-fraud transactions). These techniques aim to change the class distribution in the training dataset to improve the performance of predictive models. Commonly used resampling techniques include oversampling, undersampling, and combined sampling approaches.

2.4.2. Oversampling

Oversampling techniques, such as Synthetic Minority Over-sampling Technique (SMOTE), have shown significant promise in enhancing the effectiveness of neural networks for credit card fraud detection. It works by generating synthetic samples from the minority class of fraud transactions, and aims to achieve a more balanced distribution between fraud and non-fraud transactions.

The study by (Zhu et al., 2024) integrated SMOTE with neural networks to tackle the class imbalance in fraud detection datasets. By generating synthetic samples from the minority class of fraud transactions, SMOTE balances the dataset, allowing neural networks to learn from a more representative distribution of data. (Zhu et al., 2024) also demonstrated that this approach improves the fraud detection sensitivity and reduces false positives, thereby enhancing overall model performance. Their results showcase the importance and relevance of addressing class imbalance through oversampling techniques like SMOTE when deploying neural networks for tasks like credit card fraud detection.

2.4.3. Undersampling

Undersampling techniques offer a different approach to address class imbalance in credit card fraud detection datasets. It works by randomly reducing the number of majority class instances, and also aims to achieve a more balanced distribution between fraud and non-fraud transactions. This method focuses on retaining a subset of the majority class samples (non-fraud) while maintaining all instances of the minority class (fraud), mitigating the skewness in dataset distribution.

Studies have demonstrated the effectiveness of undersampling in improving the performance of machine learning models, including neural networks. It achieves the aim of a more balanced training set that facilitates better learning of patterns associated with fraud (Batista et al., 2004). However, undersampling may remove valuable information from the majority class, leading to a loss of generalisation capability if not carefully implemented (Kubat et al., 1997).

2.4.4. Combined Sampling

Combined sampling techniques integrate both oversampling and undersampling to address class imbalance in datasets for deep learning tasks. In the study by (Mbow et al., 2021), a combined sampling approach that uses both oversampling and undersampling techniques was applied to deep learning models including CNN. The study aims to provide a better intrusion detection system. By synthesising new minority class samples and sub-sampling the majority class, the combined sampling aims to achieve a more balanced dataset distribution. Their findings illustrate that the strategy improves the overall performance of deep learning models.

Number of words for Chapter 2: 1503

CHAPTER 3: PROJECT DESIGN

3.1. Introduction

This chapter serves as a blueprint to the final year project, providing an overview of the project's design aspect. It includes the project domain and users, and justification of the project's design choices based on their needs. It also encompasses the overall structure of the project and a roadmap for the process.

3.2. Project Domain and Users

3.2.1. Project Domain

Since the project revolves around credit card fraud detection, its domain would be finance and financial technology (fintech).

3.2.2. Project Users

In the context of credit card fraud detection, the potential users could include the following (Table 4):

Users	Explanation
Financial institutions	Banks, credit card companies, and other financial institutions are negatively impacted by credit card fraud. They may lose goodwill and trust. Hence, they may use the project to detect fraud transactions and protect their customer's accounts.
Government agencies	Government agencies oversee financial transactions and they may use the project to ensure adherence to regulations related to fraud detection and prevention.
Data analysts	Data analysts may be in charge of analysing transaction data and investigating potential fraud transactions. Hence, they may use the project to streamline and improve their workflow efficiency.
Consumers	Consumers indirectly benefit from improved fraud detection measures implemented by financial institutions. This helps them protect their financial assets and sensitive information.

Table 4: Summary of project users and explanations

3.3. Justification of Design Choices

Design choices should align with the needs and requirements of these users. For example, the project will be user-friendly for financial analysts. This will be achieved by following the best practices for coding, resulting in a clear and easy-to-understand code. Comments will also be added to enhance readability. Furthermore, visualisations will be provided during data exploration and model evaluation. This is to help users better understand and interpret the results. Additionally, accuracy and speed will be prioritised when selecting the appropriate algorithms and layers for the neural network. These design choices ensure that users can efficiently detect and respond to credit card fraud.

3.4. Overall Project Structure

This section provides an overview of the project's design and workflow. It discusses the research question, data collection and preprocessing, and model design and implementation.

3.4.1. Research Questions

The literature review highlights several key methodologies and challenges with building a deep learning model for credit card fraud detection. Various machine learning techniques and deep learning models have been applied for this problem. Studies have shown that deep learning models often outperform traditional machine learning methods due to their ability to capture complex and non-linear relationships in the data (Zhu et al., 2024; Jurgovsky et al., 2018). Furthermore, imbalanced datasets are a common issue in transaction datasets, making it difficult for models to learn its patterns associated with fraud.

Therefore, the research question is: **Which deep learning model (FNN, RNN or CNN) is most effective in detecting credit card fraud using an imbalanced dataset?** This leads to the hypotheses (Table 5):

Null Hypothesis	Alternative Hypothesis
There is no significant difference in the effectiveness of FNN, RNN, or CNN models in detecting credit card fraud using imbalanced datasets.	One of FNN, RNN, or CNN models demonstrates superior effectiveness in detecting credit card fraud using imbalanced datasets compared to the others.

Table 5: Summary of hypotheses

Another research question is: **Can a hybrid model combining FNN, RNN, and CNN architectures improve the effectiveness of fraud detection compared to using each model individually?** This leads to the hypotheses (Table 6):

Null Hypothesis	Alternative Hypothesis
There is no significant difference in the effectiveness of the hybrid model compared to FNN, RNN, or CNN models individually in detecting credit card fraud using imbalanced datasets.	The hybrid model demonstrates superior effectiveness in detecting credit card fraud using imbalanced datasets compared to any of the individual models (FNN, RNN, or CNN).

Table 6: Summary of hypotheses

3.4.2. Data Collection and Preprocessing

The models will be trained using data from the Kaggle "Credit Card Fraud Detection" dataset. The dataset will be retrieved from Kaggle, where it is made available by Machine Learning Group at ULB (Université libre de Bruxelles). This dataset contains transactions made by credit cards in September 2013 by European cardholders. It includes a total of 284,807 transactions, of which 492 are fraudulent. The data features are transformed using PCA (Principal Component Analysis) due to confidentiality issues (Machine Learning Group - ULB & Andrea, 2018). The data will undergo preprocessing steps such as (Table 7):

Preprocessing Step	**Explanation**
Handling missing values (if any)	Check for any missing values in the dataset and decide on either imputation or removal.
Scaling	Since PCA has been applied, features are likely scaled. However, features like transaction amount and time may require further scaling to prevent one from dominating.
Resampling	Address class imbalance by applying resampling techniques to the dataset.
Splitting data	The processed data will be divided into training, testing, and validation sets.

Table 7: Summary of preprocessing steps and explanations

3.4.3. Model Design

3.4.3.1. Initial Baseline Models

All baseline models are considered shallow because they are simple and consist of few layers. They are designed to establish foundational performance benchmarks.

The **Feedforward Neural Network (FNN)** baseline model starts with an input layer where each neuron receives one feature. It includes a hidden layer with 64 neurons using ReLU activation to introduce non-linearity. The output layer has a single neuron with a sigmoid activation function, indicating the likelihood of fraud.

The **Recurrent Neural Network (RNN)** baseline model processes sequential data with an input reshaped to 3D. It uses a SimpleRNN layer with 64 units to capture temporal dependencies and follows with a dense layer of 64 ReLU-activated neurons. The output layer, similar to the FNN, uses a sigmoid activation function.

The **Convolutional Neural Network (CNN)** baseline model processes data reshaped to 3D with a Conv1D layer containing 32 filters and a kernel size of 3 to detect local patterns. A MaxPooling1D layer reduces dimensionality, followed by a Flatten layer and a dense layer with 64 ReLU-activated neurons. The output layer uses a sigmoid activation function to predict fraud likelihood.

The flowcharts below summarise the baseline models, including inputs, hidden layers, and outputs (Figure 1).

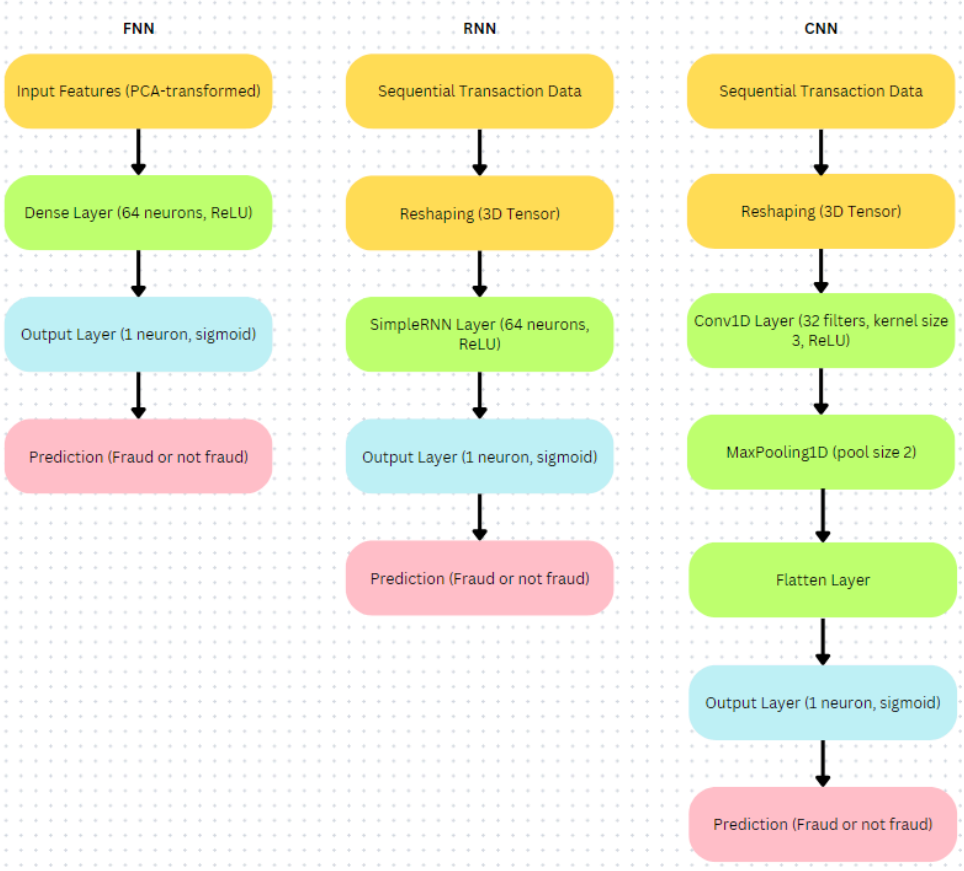

Figure 1: Flowcharts of baseline models architecture

3.4.3.2. Enhanced Models

After establishing baseline models, the next steps involve creating enhanced versions of the models to improve performance. The table below summarises ways to do so (Table 8).

Step	Explanation
Adding more layers	Add layers such as multiple convolutions, stacked RNNs, or deeper FNNs to increase model depth.
Increasing model capacity	Adjust the number of neurons or filters per layer to increase model capacity.
Applying regularisation	Use dropout, batch normalisation, or L2 regularisation to combat overfitting.
Tuning hyperparameters	Optimise learning rate, batch size, optimiser choice, and other parameters.
Replace 'SimpleRNN' with 'LSTM'	Use LSTM for better handling of long-term dependencies due to its gating mechanisms.

Table 8: Summary of steps and explanations for creating enhanced models

3.4.3.3. Basic Hybrid Model

The basic hybrid model is designed to leverage the strengths of the FNN, RNN, and CNN by combining them into a unified architecture. The **CNN** component processes input through Conv1D with 32 filters, MaxPooling1D, and Dense layers (64 neurons, ReLU). The **RNN** component uses SimpleRNN with 64 units and a Dense layer (64 neurons, ReLU). The **FNN** component includes two Dense layers (64 neurons, ReLU). These outputs are concatenated, processed through additional Dense layers with 128 and 64 neurons, and Dropout layers (0.5 rate). The final output layer has a single neuron with a sigmoid activation function.

The flowchart below summarises the basic hybrid model, including inputs, hidden layers, and outputs (Figure 2).

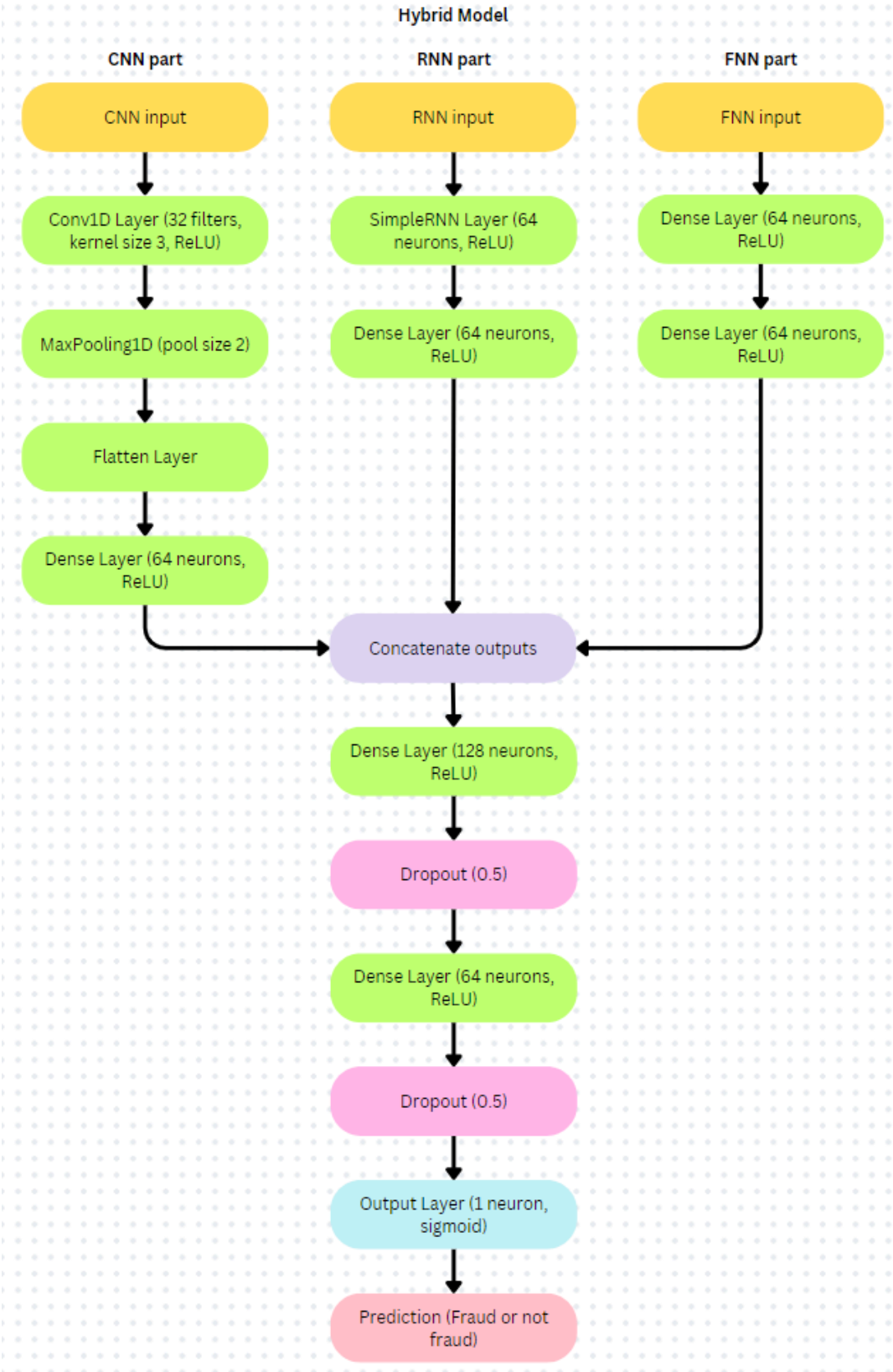

Figure 2: Flowchart of basic hybrid model architecture

3.4.3.4. Enhanced Hybrid Model

After establishing the basic hybrid model, the next steps involve creating an enhanced version of the model to improve performance. The table below summarises ways to do so (Table 9).

Step	Explanation
Increasing model capacity	Adjust the number of neurons or filters per layer to increase model capacity.
Applying regularisation techniques	Use dropout, batch normalisation, or L2 regularisation to combat overfitting.
Tuning hyperparameters	Optimise learning rate, batch size, optimiser choice, and other parameters.
Replace 'SimpleRNN' with 'LSTM'	Use LSTM for better handling of long-term dependencies due to its gating mechanisms.
Applying batch normalisation	Add 'BatchNormalization' to stabilise training and improve convergence.
Implementing early stopping	Monitor validation performance and stop training when necessary to prevent overfitting.

Table 9: Summary of steps and explanations for creating enhanced models

3.4.4. Evaluation

The models will be evaluated using performance metrics similar to the ones listed in Chapter 1.3. They include accuracy, precision, recall, and F1-score. These provide a balanced view on the model's effectiveness in detecting fraud transactions. Furthermore, training and validation loss curves will be analysed to estimate any potential underfitting or overfitting that might occur during training phases. Additionally, cross-validation techniques, such as k-fold cross-validation, will be employed to ensure the models generalise well on unseen data. Lastly, comparisons against baseline models will be made to determine if the increased complexity and enhancements result in significant improvements.

3.5. Important Technologies

3.5.1. Programming Languages

The primary programming language used is **Python**.

3.5.2. Libraries and Frameworks

The project uses **TensorFlow** and **Keras** for building the training deep learning models. TensorFlow provides a comprehensive ecosystem for developing machine learning applications, whereas Keras offers a user-friendly API for defining and training neural networks.

Scikit-learn is also used in the project for preprocessing data, implementing machine learning algorithms, and evaluating model performance. It provides simple and efficient tools for data analysis.

The project also uses **Pandas** and **NumPy**. Pandas is used for data manipulation and analysis, providing data structures like DataFrames. On the other hand, NumPy is used for numerical operations on arrays and matrices.

Matplotlib and **Seaborn** are used for data visualisations. Matplotlib is a plotting library that provides an object-oriented API for embedding plots into applications. Seaborn is built on top of Matplotlib and provides a high-level interface for drawing attractive statistical graphs.

Lastly, **Imbalance-learn (imblearn)** is used to handle imbalanced datasets. It provides techniques such as undersampling to balance the class distribution in the dataset.

3.5.3. Development Platforms

The project uses **Jupyter Notebook** for writing and executing Python code. **GitHub** is also used for version control.

3.6. Workplan

The project will be divided into various tasks spread across 20 weeks. Table 10 summarises the project workplan and activities.

Weeks	Objectives	Activities
1-2	Project Planning and Ideation	- Establish goals, define scope, create workplan - Brainstorm project idea - Define research questions and hypotheses - Identify resources needed
2-4	Literature Review	- Review relevant papers on fraud detection and deep learning - Summarise findings on models (FNN, RNN, CNN) and resampling techniques
4-5	Data Acquisition and Preprocessing	- Acquire relevant dataset - Perform EDA - Clean and preprocess data - Split data into training, validation, and test sets
6-8	Design and Implement Baseline Models	- Design and implement baseline models (FNN, RNN, CNN) - Train and validate models
8-9	Evaluate Baseline Models	- Evaluate models using metrics (accuracy, precision, recall, F1-score) - Plot loss curves - Document findings
9-10	Preliminary Report	- Compile literature review, baseline models, and evaluations - Draft preliminary report
11-13	Design and Implement Enhanced Models	- Design enhanced models with advanced techniques (LSTM, dropout, regularisation) - Train and monitor performance
13-14	Evaluate Enhanced Models	- Evaluate enhanced models using same metrics - Plot loss curves - Document insights and improvements
14-16	Design and Implement Basic Hybrid Model	- Design and implement basic hybrid model (CNN, RNN, FNN integration) - Train and validate model
16	Evaluate Basic Hybrid Model	- Evaluate hybrid model using same metrics - Plot loss curves - Document findings

16-18	Design and Implement Enhanced Hybrid Model	- Design enhanced hybrid model (batch normalisation, early stopping) - Train and monitor performance
18	Evaluate Enhanced Hybrid Model	- Evaluate enhanced hybrid model - Compare with basic hybrid model - Document insights and improvements
19	Comparison and Conclusion of Results	- Compare performance of all models - Draw conclusions about model effectiveness
19-20	Final Report	- Compile final report - Review and revise based on feedback - Finalise and submit report

Table 10: Summary of workplan with key objectives and activities

Figure 3 below summarises the breakdown of these tasks and their allocated time frames.

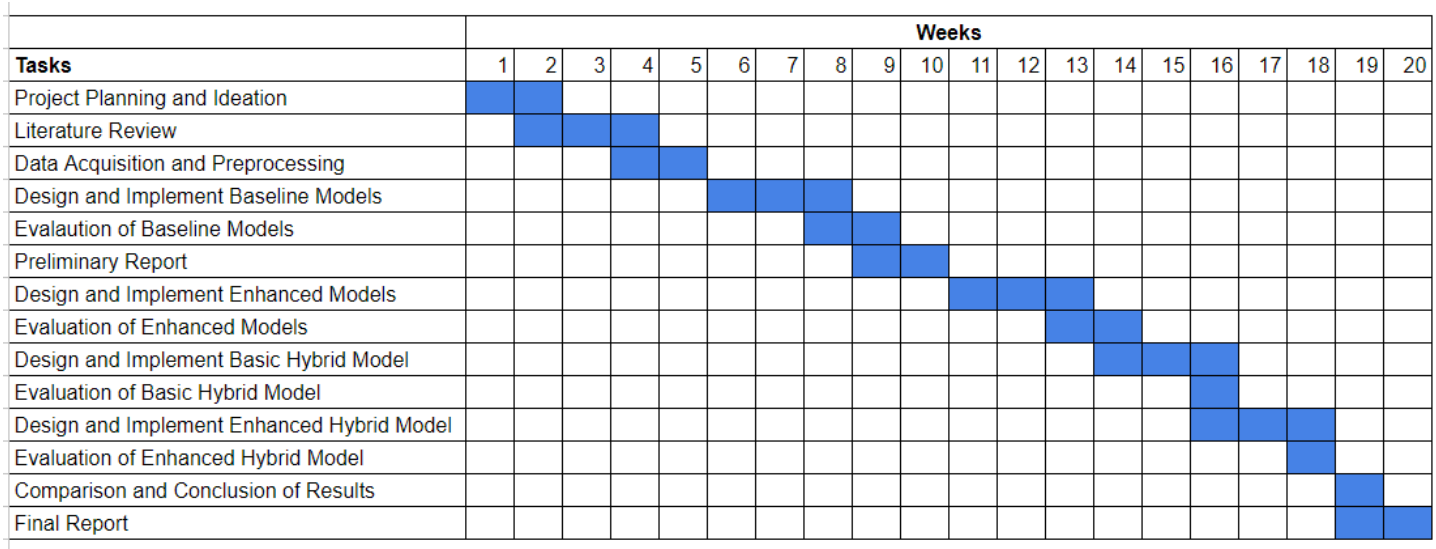

Figure 3: Gantt chart summarising workplan

Number of words for Chapter 3: 1512

CHAPTER 4: IMPLEMENTATION

4.1. Introduction

This chapter provides an overview of the implementation phase, covering exploratory data analysis (EDA), data preprocessing, model development, compilation and evaluation. It concludes with a comparison of model performance.

4.2. Data Preprocessing

4.2.1. Exploratory Data Analysis (EDA)

The project uses a credit card transaction dataset from Kaggle, provided by the Machine Learning Group at ULB (Université libre de Bruxelles). The dataset includes transactions from September 2013 by European cardholders, totaling 284,807 transactions, of which 492 are fraudulent. Due to confidentiality concerns, some features have been transformed using PCA (Principal Component Analysis) (Machine Learning Group - ULB & Andrea, 2018).

The EDA revealed a total of 30 features and 1 binary target variable ('Class'), where 0 represents non-fraud, and 1 indicates fraud. Features 'Time' and 'Amount' require scaling due to different magnitudes. No null values were found, but a significant class imbalance was noted (Figure 4). The methods for addressing this imbalance will be discussed in Chapter 4.3.

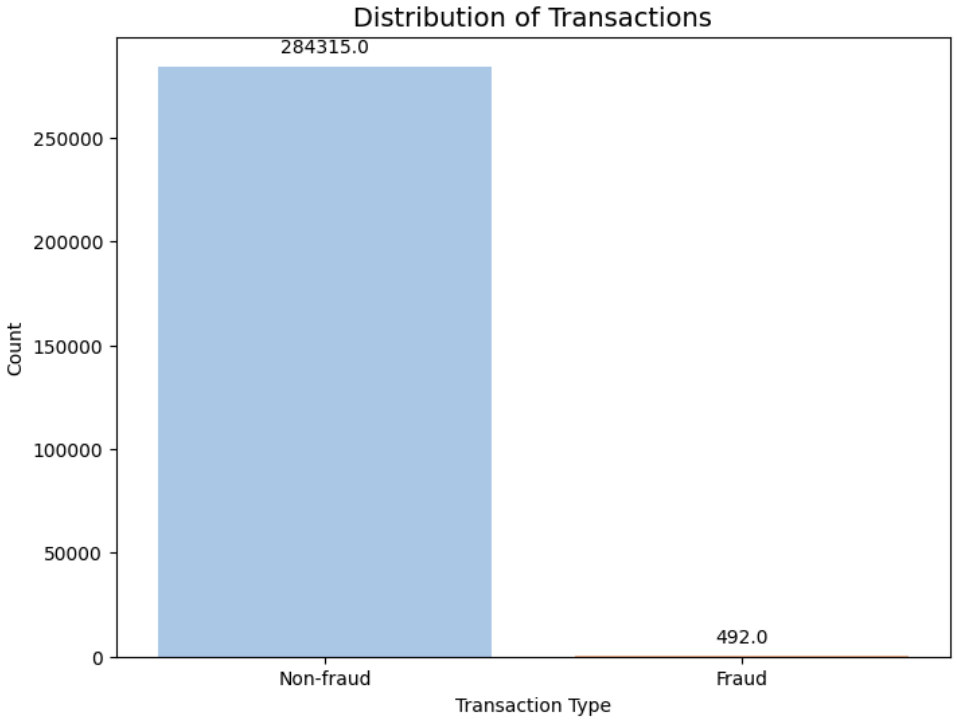

Figure 4: Count plot depicting the distribution of all transactions

4.2.2. Data Scaling

To ensure consistency, the 'Time' and 'Amount' features were scaled. Scaling is crucial because it prevents features with larger numerical ranges from dominating the model training process.

The **RobustScaler** from **sklearn.preprocessing** was chosen over **StandardScaler** as it is less sensitive to outliers. This scaler transforms the 'Time' and 'Amount' features to a range between -1 and 1, aligning them with the scaled range of other features (Figure 5). Figure 6 shows the dataframe with the scaled features.

```
# Import necessary libraries
from sklearn.preprocessing import RobustScaler # RobustScaler is less prone to outliers

# Initialize RobustScaler
scaler = RobustScaler()

# Scale 'Amount' and 'Time' features using RobustScaler
df['scaled_amount'] = scaler.fit_transform(df['Amount'].values.reshape(-1,1))
df['scaled_time'] = scaler.fit_transform(df['Time'].values.reshape(-1,1))
```

Figure 5: Code snippet of data scaling using RobustScaler

	scaled_amount	scaled_time	V1	V2	V3	V4	V5	V6
0	1.783274	-0.994983	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388
1	-0.269825	-0.994983	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361
2	4.983721	-0.994972	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499
3	1.418291	-0.994972	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203
4	0.670579	-0.994960	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921

5 rows × 31 columns

Figure 6: New dataframe with scaled features

4.2.3. Data Splitting

The dataset was split into training (70%), validation (15%), and testing (15%) sets. The **train_test_split** function was used, ensuring a balanced distribution across the splits (Figure 7). Figure 8 shows the class distribution across the sets.

```python
# Import necessary libraries
from sklearn.model_selection import train_test_split

# Separate the input features (X) and the target variable (y)
X = df_resampled.drop('Class', axis=1)
y = df_resampled['Class']

# First, split the data into training + validation set and testing set
X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

# Then, split the training + validation set into training set and validation set
X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val, test_size=0.25, random_state=42, stratify=y_train_val)
```

Figure 7: Code snippet of data splitting using train_test_split

```
Training set size: 590
Validation set size: 197
Testing set size: 197
Class distribution in training set:
Class
0    295
1    295
Name: count, dtype: int64

Class distribution in validation set:
Class
1    99
0    98
Name: count, dtype: int64

Class distribution in testing set:
Class
0    99
1    98
Name: count, dtype: int64
```

Figure 8: Training, validation, and testing set sizes and their class distribution

4.3. Handling Imbalanced Data

The EDA highlighted a severe imbalance in the dataset, with non-fraudulent transactions vastly outnumbering fraudulent ones. Given the large dataset size of nearly 300,000 data points and limited computational resources, undersampling was chosen. **RandomUnderSampler** from **imblearn.under_sampling** reduced non-fraudulent transactions to match the number of fraudulent ones, balancing the dataset for model training. This undersampling was performed prior to data splitting (Figure 9). Figure 10 illustrates the distribution of the balanced sample.

```python
# Import necessary libraries
from imblearn.under_sampling import RandomUnderSampler

# Separate the input features (X) and the target variable (y)
X = df.drop('Class', axis=1)
y = df['Class']

# Initialize the RandomUnderSampler
rus = RandomUnderSampler(random_state=42)

# Apply the undersampler to the dataset
X_res, y_res = rus.fit_resample(X, y)
```

Figure 9: Code snippet undersampling using RandomUnderSampler

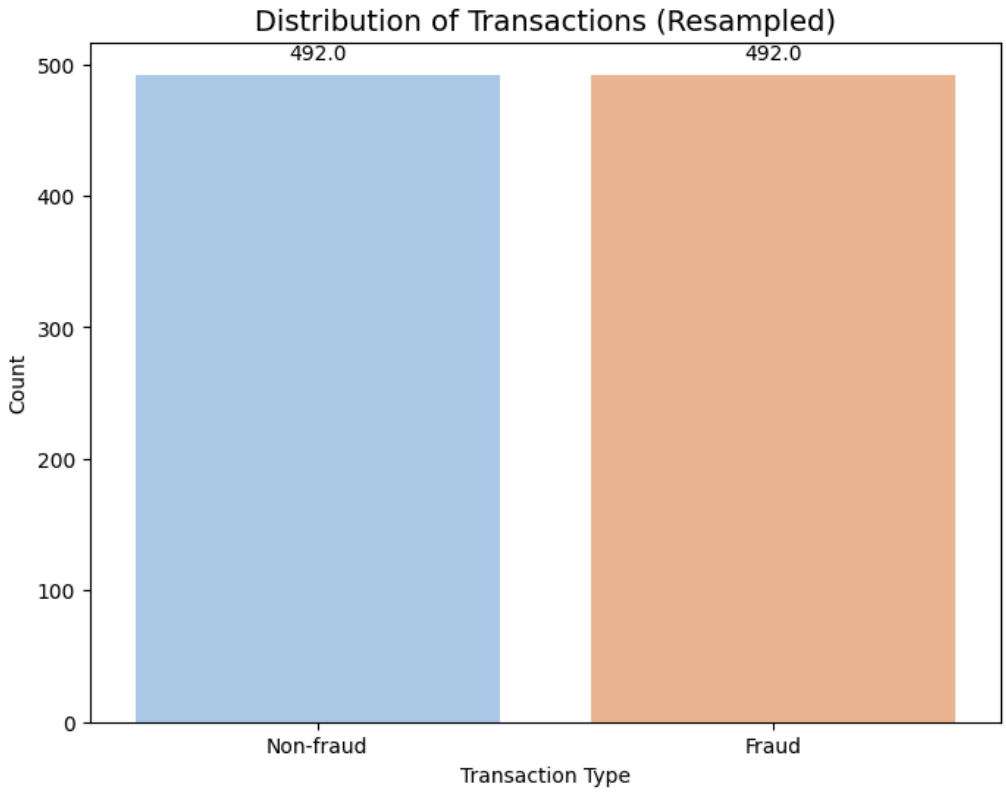

Figure 10: Count plot depicting the distribution of the balanced sample

4.4. Baseline Model Architecture

Baseline models provide a reference point for evaluating more complex models. Baseline models for Feedforward Neural Networks (FNN), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN) were implemented. A flowchart of the models' architecture can be seen in Figure 1 in Chapter 3.4.3.1.

4.4.1. Feedforward Neural Network (FNN)

A simple FNN model was implemented as the baseline. The **tensorflow** and **tensorflow.keras.models** libraries were imported to build and train the neural network, while **tensorflow.keras.layers.Dense** was used to create fully connected layers. The **sklearn.metrics.classification_report** was imported for model evaluation.

The baseline FNN model was built using the **Sequential** API from Keras with two dense layers. The first dense layer had 64 neurons with ReLU activation. The output layer had a single neuron with sigmoid activation, appropriate for binary classification tasks (Figure 11).

```
# Import necessary libraries
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.metrics import classification_report

# Create the FNN model
fnn_model = Sequential([
    Dense(64, input_dim=X_train.shape[1], activation='relu'),  # Single hidden layer
    Dense(1, activation='sigmoid')  # Output layer
])
```

Figure 11: Code snippet for the baseline FNN model implementation

4.4.2. Recurrent Neural Network (RNN)

A simple RNN model was implemented as the baseline. The input data **(X_train, X_val, X_test)** was reshaped into a 3D format suitable for RNN input. The baseline RNN model was built using a **SimpleRNN** layer with 64 units, capturing sequential patterns in the data. A dense layer was added to further learn from these patterns (Figure 12).

```
# Import necessary libraries
from tensorflow.keras.layers import SimpleRNN

# Reshape the data for RNN (reshape to 3D)
X_train_rnn = X_train.values.reshape((X_train.shape[0], 1, X_train.shape[1]))
X_val_rnn = X_val.values.reshape((X_val.shape[0], 1, X_val.shape[1]))
X_test_rnn = X_test.values.reshape((X_test.shape[0], 1, X_test.shape[1]))

# Create the RNN model
rnn_model = Sequential([
    SimpleRNN(64, input_shape=(1, X_train.shape[1]), activation='relu'),  # Single RNN layer
    Dense(1, activation='sigmoid')  # Output layer
])
```

Figure 12: Code snippet for the baseline RNN model implementation

4.4.3. Convolutional Neural Network (CNN)

A simple CNN model was implemented as the baseline. The input data **(X_train, X_val, X_test)** was reshaped into a 3D format suitable for CNN input. The baseline CNN model was implemented using a **Conv1D** layer with 32 filters, followed by a **MaxPooling1D** layer. The **input_shape** parameter was set to (30, 1) to match the number of features and class respectively. Then, a **Flatten** layer converts the 2D output to a 1D vector, which is fed into the final dense layer with sigmoid activation (Figure 13).

```
# Import necessary libraries
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten

# Reshape the data for CNN (reshape to 3D)
X_train_cnn = X_train.values.reshape((X_train.shape[0], X_train.shape[1], 1))
X_val_cnn = X_val.values.reshape((X_val.shape[0], X_val.shape[1], 1))
X_test_cnn = X_test.values.reshape((X_test.shape[0], X_test.shape[1], 1))

# Create the CNN model
cnn_model = Sequential([
    Conv1D(32, kernel_size=3, activation='relu', input_shape=(30, 1)),  # Single Conv layer
    MaxPooling1D(pool_size=2),  # Pooling layer
    Flatten(),
    Dense(1, activation='sigmoid')  # Output layer
])
```

Figure 13: Code snippet for the baseline CNN model implementation

4.5. Baseline Model Enhancements

To improve the performance of the baseline models, several enhancements were implemented. These enhancements aimed to address overfitting, improve generalisation, and better capture the underlying patterns in the data.

4.5.1. Feedforward Neural Network (FNN)

The enhanced FNN model introduced several key improvements over the baseline. The baseline model consisted of a single hidden layer with 64 neurons, whereas the enhanced model featured two hidden layers with 128 and 64 neurons, respectively, allowing for greater complexity in feature learning. Additionally, **L2 regularisation** and **Dropout** layers with a rate of 0.5 were added in the enhanced model to mitigate overfitting and improve generalisation. The output layer remained the same with a single neuron and sigmoid activation (Figure 14).

```
# Import necessary libraries
from tensorflow.keras.regularizers import l2
from tensorflow.keras.layers import Dropout

# Create the FNN model
new_fnn_model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train.shape[1],), kernel_regularizer=l2(0.01)),
    Dropout(0.5),
    Dense(64, activation='relu', kernel_regularizer=l2(0.01)),
    Dropout(0.5),
    Dense(1, activation='sigmoid')
])
```

Figure 14: Code snippet for the enhanced FNN model implementation

4.5.2. Recurrent Neural Network (RNN)

The enhanced RNN model also introduced significant improvements over the baseline. The baseline model used a single **SimpleRNN** layer with 64 units, while the enhanced model replaced this with two **Long Short Term Memory (LSTM)** layers, which are more effective at learning long-term dependencies. The first **LSTM** layer has 128 units and is configured to return sequences, enabling the second **LSTM** layer with 64 units to process the entire sequence. Additionally, **L2 regularisation** and **Dropout** layers with a rate of 0.5 were added in the enhanced model to mitigate overfitting and improve generalisation. The output layer remained the same, consisting of a single neuron with sigmoid activation for binary classification (Figure 15).

```
# Import necesssary libraries
from tensorflow.keras.layers import LSTM

# Create the RNN model
new_rnn_model = Sequential([
    LSTM(128, return_sequences=True, input_shape=(1, X_train.shape[1]), kernel_regularizer=l2(0.01), dropout=0.5),
    LSTM(64, kernel_regularizer=l2(0.01), dropout=0.5),
    Dense(1, activation='sigmoid')
])
```

Figure 15: Code snippet for the enhanced RNN model implementation

4.5.3. Convolutional Neural Network (CNN)

The enhanced CNN model builds upon the baseline. While the baseline model featured a single **Conv1D** layer with 32 filters, the enhanced model included two **Conv1D** layers with 64 and 128 filters, allowing for deeper feature extraction. Additionally, **L2 regularisation** and **Dropout** layers with a rate of 0.5 were added in the enhanced model to mitigate overfitting and improve generalisation. Finally, the dense layer before the output was expanded from 1 neuron in the baseline to 128 neurons in the enhanced model, enabling the network to learn more complex representations before making the final classification (Figure 16).

```
# Create the CNN model
new_cnn_model = Sequential([
    Conv1D(64, kernel_size=3, activation='relu', input_shape=(X_train.shape[1], 1), kernel_regularizer=l2(0.01)),
    MaxPooling1D(pool_size=2),
    Dropout(0.5),
    Conv1D(128, kernel_size=3, activation='relu', kernel_regularizer=l2(0.01)),
    MaxPooling1D(pool_size=2),
    Dropout(0.5),
    Flatten(),
    Dense(128, activation='relu', kernel_regularizer=l2(0.01)),
    Dropout(0.5),
    Dense(1, activation='sigmoid')
])
```

Figure 16: Code snippet for the enhanced CNN model implementation

4.6. Basic Hybrid Model Architecture

To leverage the strengths of FNN, RNN, and CNN, a hybrid model was developed. This model combines the spatial feature extraction capabilities of CNNs, the sequential pattern recognition of RNNs, and the general feature learning of FNNs. The hybrid model aims to capture diverse aspects of the data, improving predictive performance and robustness in detecting credit card fraud. A flowchart of the models' architecture can be seen in Figure 2 in Chapter 3.4.3.3.

4.6.1. Input Layers

Three separate input layers are defined to feed data into the respective sub-networks (Table 10). Figure 17 shows the code snippet to do so.

Input Layer	Explanation
CNN	Takes data with the shape **(X_train.shape[1], 1)**, where **X_train.shape[1]** corresponds to the number of features.
RNN	Takes data with the shape **(1, X_train.shape[1])**
FNN	Takes data in the shape **(X_train.shape[1],)**

Table 10: Input layers and their explanations

```
# Import necessary libraries
from tensorflow.keras.layers import Input, concatenate
from tensorflow.keras.models import Model

# Define the input layers
input_layer_cnn = Input(shape=(X_train.shape[1], 1))
input_layer_rnn = Input(shape=(1, X_train.shape[1]))
input_layer_fnn = Input(shape=(X_train.shape[1],))
```

Figure 17: Code snippet for defining input layers

4.6.2. CNN Component

The CNN component consists of four layers (Table 11). Figure 18 shows the code snippet to do so.

Layer	Explanation
Convolutional Layer	A **Conv1D** layer with 32 filters and a kernel size of 3 is applied to the input, extracting spatial features.
Pooling Layer	A **MaxPooling1D** layer with a pool size of 2 down-samples the feature maps, reducing the dimensionality.
Flattening Layer	The output is then flattened to convert the 2D feature maps into a 1D vector.
Dense Layer	A dense layer with 64 neurons and ReLU activation is added to further learn from the features.

Table 11: CNN component layers and their explanation

```
# CNN part
cnn = Conv1D(32, kernel_size=3, activation='relu')(input_layer_cnn)
cnn = MaxPooling1D(pool_size=2)(cnn)
cnn = Flatten()(cnn)
cnn_output = Dense(64, activation='relu')(cnn)
```

Figure 18: Code snippet for the CNN component

4.6.3. RNN Component

The RNN component consists of two layers (Table 12). Figure 19 shows the code snippet to do so.

Layer	Explanation
RNN Layer	A **SimpleRNN** layer with 64 units is applied to the RNN input, capturing sequential patterns in the data.
Dense Layer	A dense layer with 64 neurons and ReLU activation is added to further learn from the features.

Table 12: RNN component layers and their explanation

```
# RNN part
rnn = SimpleRNN(64, activation='relu')(input_layer_rnn)
rnn_output = Dense(64, activation='relu')(rnn)
```

Figure 19: Code snippet for the RNN component

4.6.4. FNN Component

The FNN component consists of two layers (Table 13). Figure 20 shows the code snippet to do so.

Layer	Explanation
Dense Layer	A dense layer with 64 neurons and ReLU activation is applied to the FNN input.
Dense Layer	A dense layer with 64 neurons and ReLU activation is added to further learn from the features.

Table 13: FNN component layers and their explanation

```
# FNN part
fnn = Dense(64, activation='relu')(input_layer_fnn)
fnn_output = Dense(64, activation='relu')(fnn)
```

Figure 20: Code snippet for the FNN component

4.6.5. Concatenation and Output Layer

The outputs from the CNN, RNN, and FNN components are concatenated into a single tensor. This step combines the spatial, sequential, and general features learned by each sub-network. The concatenated features are then passed through a series of dense layers. The first dense layer has 128 neurons with ReLU activation, followed by a dropout layer with a rate of 0.5 to prevent overfitting. This is followed by another dense layer with 64 neurons and another dropout layer. The final output layer consists of a single neuron with sigmoid activation. Figure 21 shows the code snippet to do so.

```
# Concatenate the outputs
concatenated = concatenate([cnn_output, rnn_output, fnn_output])

# Add a few dense layers for learning from combined features
x = Dense(128, activation='relu')(concatenated)
x = Dropout(0.5)(x)
x = Dense(64, activation='relu')(x)
x = Dropout(0.5)(x)

# Final output layer
output_layer = Dense(1, activation='sigmoid')(x)
```

Figure 21: Code snippet for the concatenation and output layer

4.7. Hybrid Model Enhancements

The enhanced hybrid model introduces several improvements over the basic version, focusing on regularisation and normalisation techniques to further refine the learning process. Table 14 summarises these improvements and Figure 22 shows the code snippet for the enhanced hybrid model.

Feature	Basic Hybrid Model	Enhanced Hybrid Model
Regularisation	None	L2 regularisation applied to CNN, RNN, and FNN components, and dense layers.
Normalisation	Not used	BatchNormalisation added to the FNN component and dense layers.
CNN Component	Conv1D with 32 filters, kernel size 3; MaxPooling1D; Dense with 64 neurons.	Conv1D with 32 filters, kernel size 3; MaxPooling1D; Dense with 32 neurons.
RNN Component	SimpleRNN with 64 units; Dense with 64 neurons.	LSTM with 32 units; Dense with 32 neurons.
FNN Component	Dense with 64 neurons; Dense with 64 neurons.	Dense with 64 neurons; BatchNormalization; Dense with 32 neurons.
Dense Layers after Concatenation	Dense layers with 128 and 64 neurons.	Dense layers with 64 and 32 neurons.
EarlyStopping	Not used	EarlyStopping included to optimise training.

Table 14: Summary of the hybrid model improvements

```
# Import necessary libraries
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.callbacks import EarlyStopping

# CNN part with L2 regularization
cnn = Conv1D(32, kernel_size=3, activation='relu', kernel_regularizer=l2(0.01))(input_layer_cnn)
cnn = MaxPooling1D(pool_size=2)(cnn)
cnn = Flatten()(cnn)
cnn_output = Dense(32, activation='relu', kernel_regularizer=l2(0.01))(cnn)

# RNN part with L2 regularization
rnn = LSTM(32, kernel_regularizer=l2(0.01), return_sequences=False)(input_layer_rnn)
rnn_output = Dense(32, activation='relu', kernel_regularizer=l2(0.01))(rnn)

# FNN part with L2 regularization and Batch Normalization
fnn = Dense(64, activation='relu', kernel_regularizer=l2(0.01))(input_layer_fnn)
fnn = BatchNormalization()(fnn)
fnn_output = Dense(32, activation='relu', kernel_regularizer=l2(0.01))(fnn)

# Concatenate the outputs
concatenated = concatenate([cnn_output, rnn_output, fnn_output])

# Add dense layers with L2 regularization and Batch Normalization
x = Dense(64, activation='relu', kernel_regularizer=l2(0.01))(concatenated)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
x = Dense(32, activation='relu', kernel_regularizer=l2(0.01))(x)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)

# Final output layer
output_layer = Dense(1, activation='sigmoid', kernel_regularizer=l2(0.01))(x)
```

```
# Define early stopping
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)
```

Figure 22: Code snippet of the enhanced hybrid model implementation

4.8. Model Compilation

All models, including the enhanced hybrid model, were compiled using the **Adam optimizer**, **binary crossentropy loss**, and **accuracy** as the **evaluation metric**. The Adam optimizer was chosen for its adaptive learning rate capabilities, which helped in efficiently navigating the optimisation landscape. Binary crossentropy was selected as the loss function since the task at hand is binary classification—specifically, credit card fraud detection. Accuracy was used as the metric to evaluate the performance of the models, providing a clear indication of how well the model classifies fraud versus non-fraud transactions (Figure 23).

```
# Compile the model
new_hybrid_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

Figure 23: Code snippet for enhanced hybrid model compilation

4.9. Model Training and Evaluation

All models, including the enhanced hybrid model, were trained for 10 epochs with a batch size of 32. The training process involved fitting the model using the respective input formats, along with the training labels. Validation data was provided to monitor the model's performance on unseen data during training. After training, the model's performance was evaluated on the test set to assess its ability to generalise to new data. Predictions were generated by applying a threshold of 0.5 to the output probabilities, converting them into binary class labels. This approach assessed the model's accuracy and effectiveness in distinguishing between fraudulent and non-fraudulent transactions (Figure 24).

```
# Train the model
history_hybrid = hybrid_model.fit(
    [X_train_cnn, X_train_rnn, X_train], y_train,
    epochs=10, batch_size=32,
    validation_data=([X_val_cnn, X_val_rnn, X_val], y_val)
)

# Evaluate the model
y_pred_hybrid = (hybrid_model.predict([X_test_cnn, X_test_rnn, X_test]) > 0.5).astype("int32")
```

Figure 24: Code snippet for enhanced hybrid model compilation

4.10. Comparison of Model Performance

The models were evaluated using performance metrics including accuracy, precision, recall, and F1-score (Table 15). For the enhanced hybrid model, additional evaluation steps were taken to ensure robustness and reliability. Specifically, confusion matrices were generated to show the distribution of true positives, true negatives, false positives, and false negatives (Figure 25). Furthermore, k-fold cross-validation was conducted for both hybrid models to validate them across multiple data splits (Figure 26). The results will be analysed in detail in Chapter 5.

Model	Accuracy	Precision	Recall	F1-score
Baseline FNN	0.95	0.95	0.95	0.95
Enhanced FNN	0.96	0.96	0.96	0.96
Baseline RNN	0.95	0.95	0.95	0.95
Enhanced RNN	0.95	0.95	0.95	0.95
Baseline CNN	0.95	0.95	0.95	0.95
Enhanced CNN	0.95	0.95	0.95	0.95
Basic Hybrid	0.93	0.93	0.93	0.93
Enhanced Hybrid	0.96	0.96	0.96	0.96

Table 15: Summary of all models' performance metrics

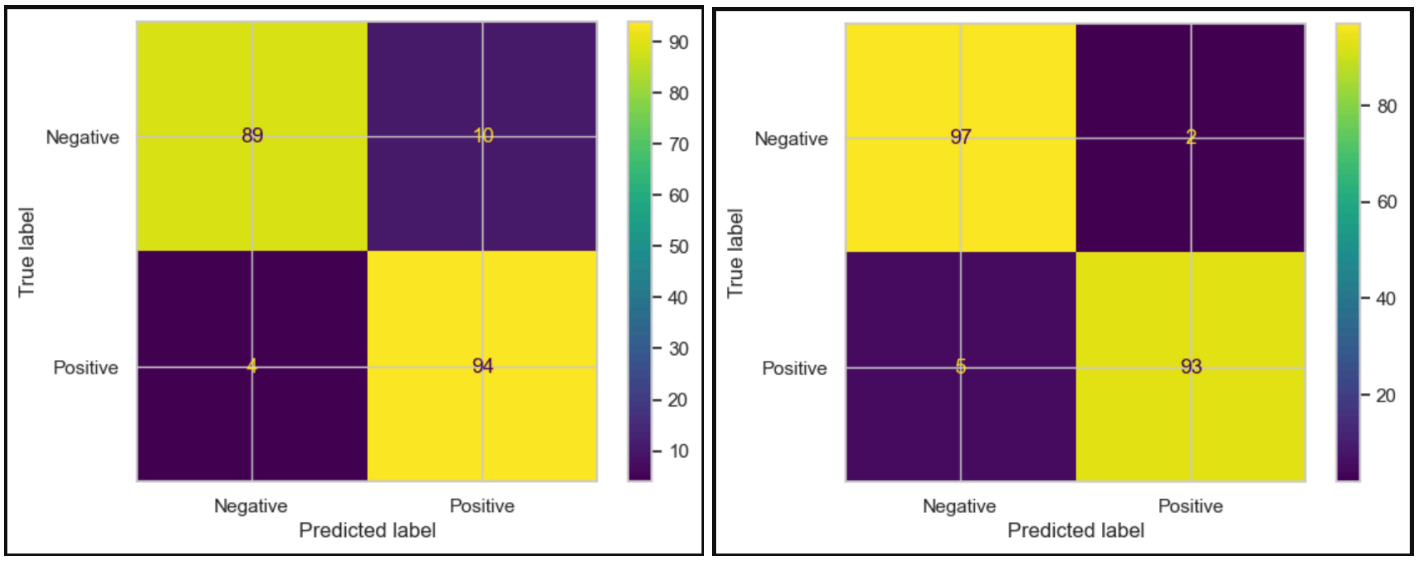

Figure 25: Confusion matrix for the basic and enhanced hybrid models respectively

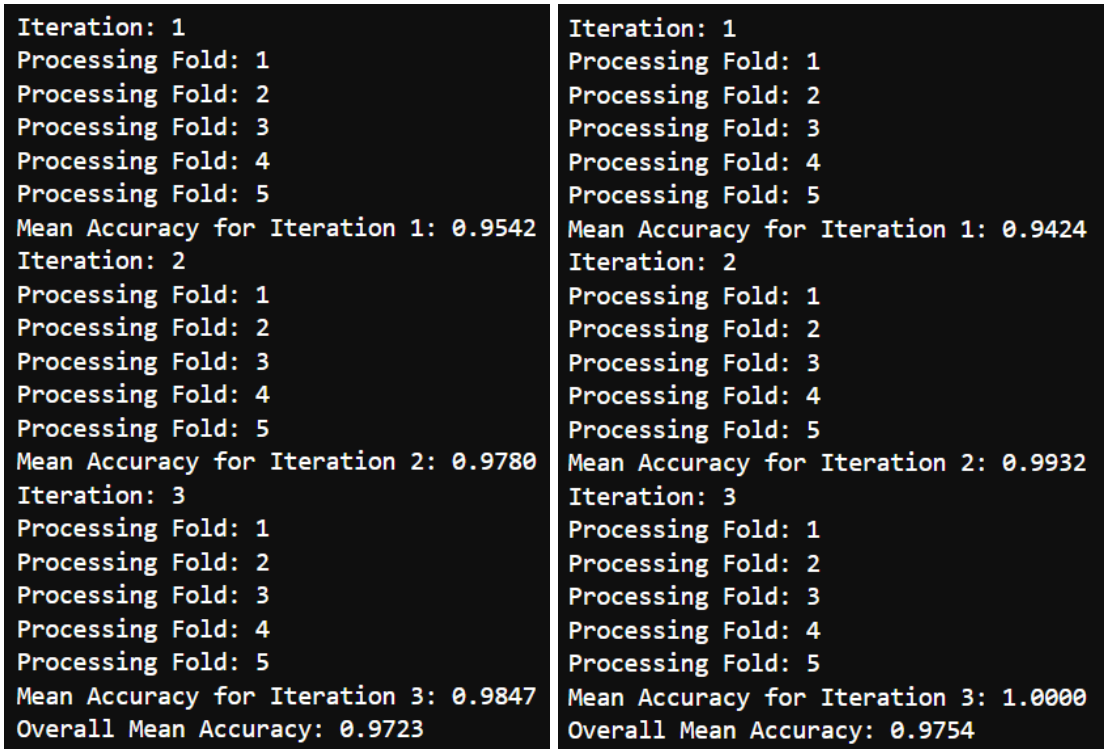

Figure 26: Results of K-fold cross-validation on the basic and enhanced hybrid models respectively

Number of words for Chapter 4: 1804

CHAPTER 5: EVALUATION

5.1. Introduction

This chapter evaluates the performance of baseline and enhanced models for credit card fraud detection, both individually and in combination. Key metrics such as accuracy, precision, recall, and F1-score will be used to assess effectiveness. Training and validation loss curves will be analysed to identify overfitting and generalisation ability, which is crucial for detecting new fraud patterns. Additionally, confusion matrix analysis will be conducted for hybrid models to examine their classification accuracy. K-fold cross-validation will provide a more reliable performance estimate by assessing the models across various data splits, reducing the risk of overfitting. This chapter will also address the research questions from Chapter 3.4.1.

5.2. Baseline vs. Enhanced Models

5.2.1. FNN

The baseline FNN model achieved an accuracy of 0.95, while the enhanced FNN model improved to 0.96. Precision and recall also increased from 0.95 to 0.96, indicating the enhanced model is slightly better at minimising false positives and detecting actual fraud transactions. The F1-score similarly improved from 0.95 to 0.96, further highlighting the enhanced model's balanced performance between precision and recall (Table 16).

Metric	Baseline	Enhanced
Accuracy	0.95	0.96
Precision	0.95	0.96
Recall	0.95	0.96
F1-score	0.95	0.96

Table 16: Table of FNN models' performance metrics

Despite the identical metrics, the loss curves provide further insight. The baseline FNN model's loss ranged from 0.15 to 0.55, with intersecting curves suggesting potential overfitting, meaning the model might perform well on training data but could struggle with unseen data. The enhanced model's losses, though higher, showed no intersections, indicating better stability and generalisation to unseen transactions. This stability makes the enhanced FNN model more reliable in real-world scenarios where the system needs to generalise to unpredictable data (Figure 27).

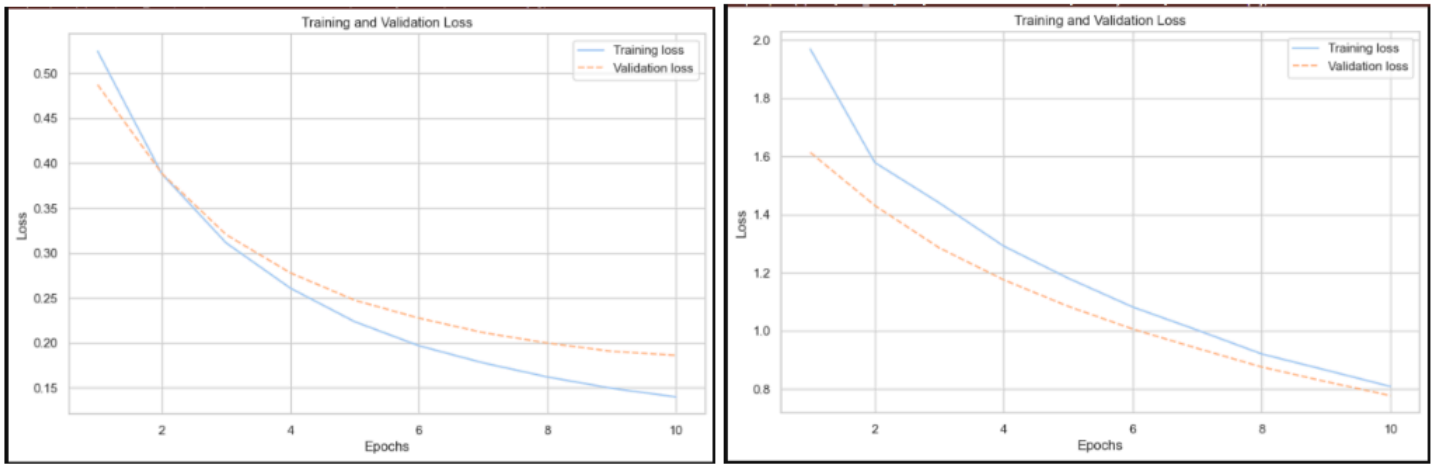

Figure 27: Training and validation loss curves for the baseline FNN model and enhanced FNN model respectively

5.2.2. RNN

Both baseline and enhanced RNN models achieved an accuracy of 0.95, with precision, recall, and F1-scores remaining consistent at 0.95 (Table 17).

Metric	Baseline	Enhanced
Accuracy	0.95	0.95
Precision	0.95	0.95
Recall	0.95	0.95
F1-score	0.95	0.95

Table 17: Table of RNN models' performance metrics

The baseline RNN's losses ranged from 0.1 to 0.6, with intersecting curves suggesting overfitting. The enhanced RNN's losses started at 0.25, with no intersections, indicating better stability and potential for generalisation (Figure 28).

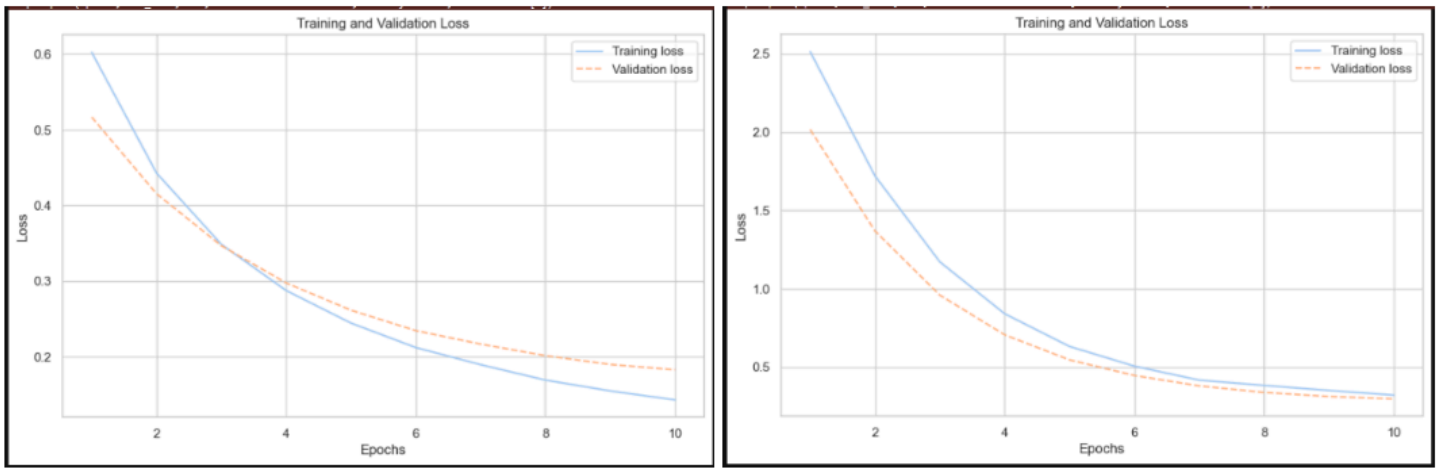

Figure 28: Training and validation loss curves for the baseline RNN model and enhanced RNN model respectively

5.2.3. CNN

Both baseline and enhanced CNN models achieved an accuracy of 0.95, with precision, recall, and F1-scores steady at 0.95 (Table 17).

Metric	Baseline	Enhanced
Accuracy	0.95	0.95
Precision	0.95	0.95
Recall	0.95	0.95
F1-score	0.95	0.95

Table 18: Table of CNN models' performance metrics

The baseline CNN's losses ranged from 0.2 to 0.7, with intersecting curves suggesting overfitting. The enhanced CNN's losses started at 0.6, with no intersections, indicating better stability and generalisation (Figure 29).

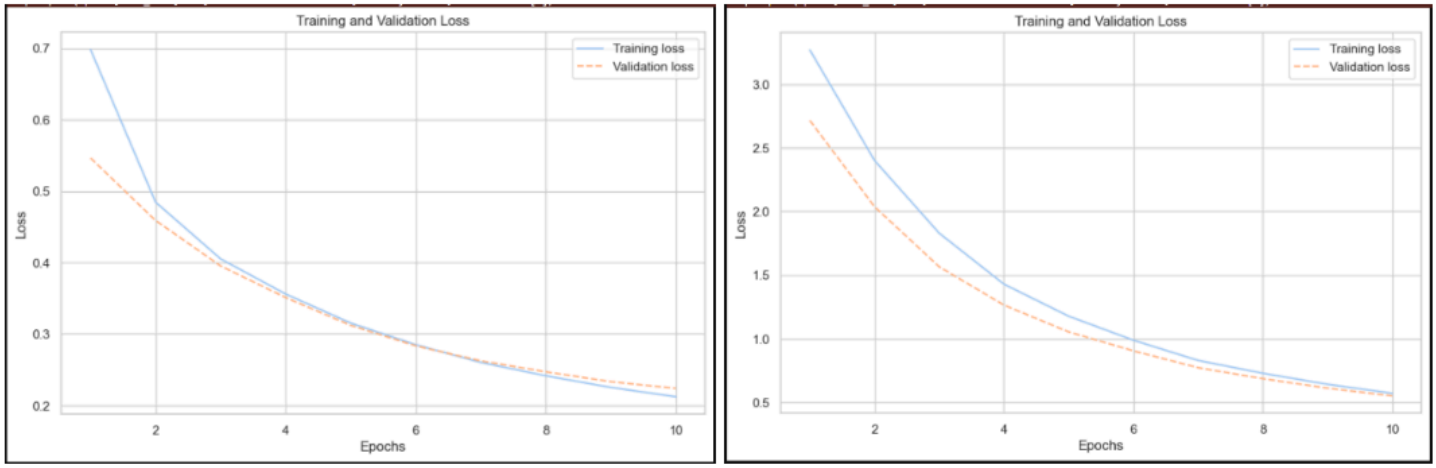

Figure 29: Training and validation loss curves for the baseline CNN model and enhanced CNN model respectively

5.3. Addressing the First Research Question

To answer the first research question, "**Which deep learning model (FNN, RNN, or CNN) is most effective in detecting credit card fraud using an imbalanced dataset?**", the performance of the models were evaluated. All models (FNN, RNN, and CNN) demonstrated comparable accuracy, precision, recall, and F1-scores, with values consistently around 0.95 and 0.96. This suggests that all models are effective in detecting credit card fraud using an imbalance dataset, with each model correctly identifying and classifying approximately 95% of the transactions. However, while the metrics are similar, the analysis of the training and validation loss curves offers additional insights into the models' stability during training and potential for generalisation.

Overall, while all models performed similarly in terms of evaluation metrics, the **enhanced FNN model** seems to be slightly more effective in handling the imbalance dataset based on both the metrics and loss curves. The enhanced FNN model's slight improvements in precision and its stable loss curves suggest that it may offer a better balance between classification performance and generalisation. This makes it the most effective model among the rest for detecting credit card fraud.

5.4. Basic vs. Enhanced Hybrid Model

5.4.1. Performance Metrics Comparison

The basic hybrid model achieved an accuracy of 0.93, while the enhanced model slightly improved to 0.96, indicating that the enhanced model is better at correctly classifying transactions as either fraud or non-fraud. Both models showed high precision, with the basic model at 0.93 and the enhanced model at 0.96. This suggests that the enhanced model flags fewer legitimate transactions as fraud. The recall also improved from 0.93 in the basic model to 0.96 in the enhanced model, indicating that the enhanced model is better at identifying actual fraudulent transactions. The F1-score increased from 0.93 to 0.96, indicating that the enhanced model provides a slightly better overall performance (Table 19).

Metric	Baseline	Enhanced
Accuracy	0.93	0.96
Precision	0.93	0.96
Recall	0.93	0.96
F1-score	0.93	0.96

Table 19: Table of hybrid models' performance metrics

The training and validation loss curves for the basic hybrid model range from 0.1 to 0.55. However, these curves intersect, particularly after epoch 3, where the validation loss begins to increase. This suggests that the basic hybrid model is prone to overfitting, meaning it performs well on training data but struggles to generalise to new, unseen data. The increase in validation loss after epoch 5 indicates that the model starts to lose its effectiveness as training progresses. In contrast, the enhanced hybrid model showed a high loss, with the lowest being around 1.0 to 2.0. However, the curves do not intersect but come close to each other, indicating better stability and reduced overfitting. This suggests that the enhanced model is likely to generalise better to new data (Figure 30).

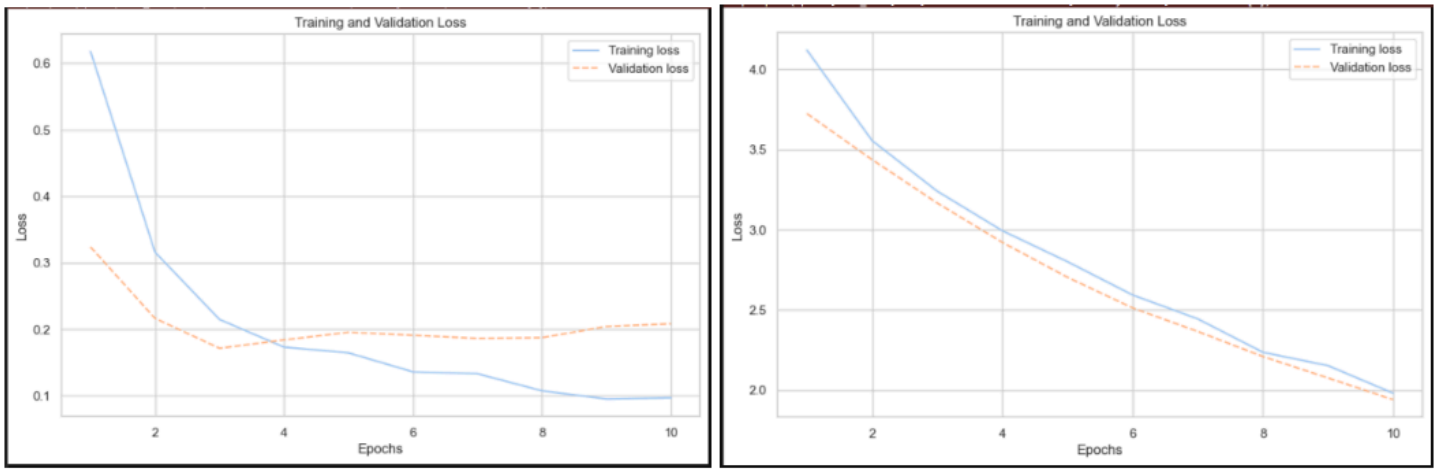

Figure 30: Training and validation loss curves for the basic hybrid model and enhanced hybrid model respectively

5.4.2. Confusion Matrix Analysis

Figure 25 in Chapter 4.10. shows the confusion matrices for both the basic and enhanced hybrid models.

For the basic hybrid model, 94 fraud transactions were correctly identified as fraud and 89 non-fraud transactions were correctly classified as non-fraud. Furthermore, 10 non-fraud transactions were incorrectly flagged as fraud and 4 fraud transactions were missed and incorrectly classified as non-fraud. This indicates that while the basic hybrid model is effective at detecting fraud, it has a slightly higher tendency to flag non-fraud transactions as fraud (Table 20).

	Predicted non-fraud	**Predicted fraud**
Actual non-fraud	89	10
Actual fraud	4	94

Table 20: Confusion matrix for the basic hybrid model

For the enhanced hybrid model, 93 fraud transactions were correctly identified as fraud and 97 non-fraud transactions were correctly classified as non-fraud. Furthermore, 2 non-fraud transactions were incorrectly flagged as fraud and 5 fraud transactions were missed and incorrectly classified as non-fraud (Table 21). The enhanced hybrid model showed a significant improvement in flagging fewer transactions as fraud. However, the enhanced model missed one more fraud case than the basic model.

	Predicted non-fraud	**Predicted fraud**
Actual non-fraud	97	2
Actual fraud	5	93

Table 21: Confusion matrix for the enhanced hybrid model

This difference reflects the balance between precision and recall: the basic hybrid model prioritises recall, successfully identifying slightly more fraud cases, while the enhanced hybrid model prioritises precision by minimising false positives. The choice between these models may depend on the specific use case. In scenarios where minimising false positives is more important (i.e., reducing customer complaints), the enhanced model would be preferred. Conversely, if identifying every possible fraud case is more important, the basic hybrid model's higher recall might be more suitable.

5.4.3. K-Fold Cross-Validation Results

Figure 26 in Chapter 4.10. shows the k-fold cross-validation results for both the basic and enhanced hybrid models. Cross-validation provides a more robust evaluation by dividing the data into multiple subsets, training the models on different subsets, and averaging the results.

The basic hybrid model showed consistently high accuracy, with a slight increase across iterations, and achieved an overall mean accuracy of 0.9723. On the other hand, the enhanced hybrid model started with a slightly lower accuracy in the first iteration (0.9424) but improved significantly in later iterations, reaching 1.0000 in the third iteration. Its mean accuracy is 0.9754, slightly higher than the basic model (Table 22). This indicates that the enhanced model may generalise slightly better across different data splits as compared to the basic model.

	Accuracy for basic hybrid model	**Accuracy for enhanced hybrid model**
Iteration 1	0.9542	0.9424
Iteration 2	0.9780	0.9932
Iteration 3	0.9847	1.0000
Mean	0.9723	0.9754

Table 22: K-fold cross-validation results for both hybrid models

5.4.4. Summary

Overall, the **enhanced hybrid model** provides better stability, generalisation, and precision while maintaining high recall, making it more reliable for real-world credit card fraud detection. The enhanced model strikes a good balance between reducing false positives and detecting actual fraud cases, which is essential in reducing both customer disruptions and financial losses.

5.5. Addressing the Second Research Question

To answer the second research question, "**Can a hybrid model combining FNN, RNN, and CNN architectures improve the effectiveness of fraud detection compared to using each model individually?**", the performance of the hybrid models was evaluated against individual baseline and enhanced models.

The results demonstrate that the hybrid models—both basic and enhanced—are able to leverage the strengths of FNN, RNN, and CNN architectures to offer improved overall performance compared to individual models. While the individual models performed similarly in key metrics (accuracy, precision, recall, and F1-score), the **enhanced hybrid model** outperformed all of them, achieving 0.96. This represents a slight improvement in classification performance, indicating that the hybrid model can better detect fraudulent transactions and reduce false positives when compared to the individual FNN, RNN, and CNN models. Moreover, the loss curves of the enhanced hybrid model did not intersect and showed reduced overfitting, highlighting its potential to generalise better to unseen data.

In summary, the results confirm that hybrid models provide enhanced performance in detecting credit card fraud. The hybrid model, by combining features learned through the different architectures, can better capture both temporal dependencies (through the RNN) and spatial hierarchies (through the CNN), while the FNN layers help in efficient classification. The combination of FNN, RNN, and CNN components within a hybrid framework offers better generalisation and improved precision and recall metrics, making the hybrid model more effective for this task than using each model individually.

Number of words for Chapter 5: 1482

CHAPTER 6: CONCLUSION

6.1. Project Summary

The project title is "Credit Card Fraud Detection Using Neural Networks".

6.1.1. Objectives

The primary goal of this project is to develop a highly accurate neural network model for detecting fraudulent credit card transactions. The model aims to achieve high performance metrics, including accuracy, precision, recall, and F1-score, while minimising training and validation losses. Additionally, the project addresses the challenge of imbalanced data (a common issue in fraud detection datasets) by applying resampling techniques.

6.1.2. Data and Methodology

The dataset used in this project is from Kaggle, consisting of 284,807 transactions from European cardholders, with only 492 classified as fraudulent (Machine Learning Group - ULB & Andrea, 2018). To handle the class imbalance, undersampling was employed to balance the number of fraud and non-fraud transactions. Data preprocessing involved exploratory data analysis (EDA), feature scaling using RobustScaler, and splitting the dataset into training, validation, and testing sets.

6.1.3. Model Development

The project explored various deep learning architectures, including Feedforward Neural Networks (FNN), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN). In addition to developing baseline versions of these models, enhanced versions were created by incorporating regularisation techniques and dropout. This was done to improve performance and generalisation. Furthermore, two hybrid models were developed: a basic hybrid model and an enhanced hybrid model. The basic hybrid model combined FNN, RNN, and CNN components, while the enhanced hybrid model integrated advanced techniques and optimisations.

6.1.4. Evaluation

Model performance was assessed using key metrics: accuracy, precision, recall, and F1-score. The baseline and enhanced models were compared, with enhanced models demonstrating slight improvements in performance. Training and validation loss curves were also analysed to identify overfitting and stability. Confusion matrix analysis highlighted differences in false positives and false negative rates between models. K-fold cross-validation further validated the models' robustness with the enhanced hybrid model showing the highest accuracy and stability.

6.1.5. Findings

FNN, RNN, and CNN models performed similarly, with enhanced versions showing marginal improvements in precision and recall. The enhanced FNN model emerged as the most effective model based on metrics and loss curves. Additionally, the enhanced hybrid model outperformed both the basic hybrid model and individual models. It achieved the highest accuracy and demonstrated better stability and generalisation. The hybrid model effectively combined the strengths of FNN, RNN, and CNN, leading to improved performance in detecting fraud transactions.

The project hence confirms that hybrid deep learning models provide superior performance compared to individual models for credit card fraud detection. The enhanced hybrid model offers a balanced approach, improving precision and recall while maintaining high accuracy. This combination effectively addresses the challenges of imbalanced data and generalisation, making it a robust solution for real-world fraud detection scenarios.

6.2. Improvements and Future Work

6.2.1. Exploring Additional Sampling Techniques

Alternative resampling methods like Synthetic Minority Over-sampling Technique (SMOTE) could be used to address the class imbalance. SMOTE generates synthetic samples of the minority class (fraud transactions), potentially improving model performance by creating a more balanced training dataset. This approach could provide a richer and more diverse set of examples for the model, potentially improving its ability to detect fraud more accurately.

6.2.2. Experimenting with Other Hybrid Architectures

Further development of the hybrid models could involve experimenting with different combinations or configurations of FNN, RNN, and CNN components. Additionally, incorporating other advanced architectures, such as Transformer-based models or attention mechanisms, might improve model performance. These architectures might capture complex patterns and dependencies in transaction data more effectively, leading to improved detection performance.

6.2.3. Advanced Model Tuning

Hyperparameter optimisation using techniques like Grid Search or Random Search could be employed to find the most effective model parameters. This process involves systematically exploring different hyperparameter values, such as learning rates, batch sizes, and regularisation parameters, to identify the most effective settings for fraud detection. Fine-tuning these parameters could lead to better model accuracy and generalisation, making the fraud detection system more robust.

6.2.4. Real-World Validation and Deployment

Evaluating the models in real-world scenarios and deploying them in a production environment would provide practical insights into their effectiveness and robustness. This involves integrating the models into an operational fraud detection system and continuously monitoring their performance. Real-world validation would help assess how well the models perform under actual transaction conditions and adjust them as needed to maintain high detection accuracy and minimise false positives.

6.3. Practical Implications

The results of this project offer valuable insights for various stakeholders. Financial institutions, such as banks and credit card companies, can leverage the developed models to enhance their fraud detection capabilities. Hence, they can preserve their reputation and safeguard customers' accounts. Government agencies can use these models to ensure compliance with regulations related to fraud detection and prevention, thereby helping them monitor financial transactions. Data analysts may find the models valuable for streamlining their workflows and improving efficiency in investigating potential fraud cases. Finally, consumers indirectly benefit from these advancements as they can better protect their financial assets and sensitive information, resulting in greater peace of mind and trust in financial services.

Number of words for Chapter 6: 836

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