Pattern recognition using LSTM in financial sectors

Msc Research Project
Msc Artificial Intelligence

Neha Manivannan
Student ID: x22175156

School of Computing
National College of Ireland

Supervisor: Muslim Jameel Syed

National College of Ireland
Project Submission Sheet
School of Computing

Student Name:	Neha Manivannan
Student ID:	x22175156
Programme:	Msc Artificial Intelligence
Year:	2023
Module:	Msc Research Project
Supervisor:	Muslim Jameel Syed
Submission Due Date:	31/01/2024
Project Title:	Pattern recognition using LSTM in financial sectors
Word Count:	7317
Page Count:	19

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.

ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature:	Neha Manivannan
Date:	31st January 2024

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST:

Attach a completed copy of this sheet to each project (including multiple copies).	☐
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	☐
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	☐

Assignments that are submitted to the Programme Coordinator office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Pattern recognition using LSTM in financial sectors

Neha Manivannan
x22175156

Abstract

This project looks into how Artificial Intelligence (AI) can be used in government work. It's about finding the right mix between using new technology and being careful about things like keeping data private and safe. The main part of the study was making and testing a special computer model that can handle and understand detailed bank transaction data. The model uses a smart method called Long Short-Term Memory (LSTM) networks, showing that AI can improve the way we analyze data, a job usually done by people. The study shows two sides of using AI in government. Firstly, AI is great for doing complex jobs by itself, making things faster, and finding important details that might be missed by people. But, it also points out worries about keeping data private and the dangers of using AI wrongly, especially with the kind of private information that governments handle. In this project, we see that our encrypted data can be decrypted by hackers or terrorists these days. It is really for the government and securities to keep our financial details more safe and secure. This study adds a lot to both learning about and using AI in government work. It shows how important it is to protect data well and use AI in a good and fair way. For researchers, it opens up new areas to explore about AI's role in government. For businesses, it creates chances for software firms and AI consulting services to help government agencies work better, but with a strong focus on keeping data safe and private. Overall, the project points out that AI can be used anywhere it can be misused by hackers or terrorists or can be safely used by the government, thinking about these its good points and possible dangers.

1 Introduction

These days many people depend on online transactions and paying bills online. This makes terrorists and hackers work simply to get the individuals' decrypted details to find the encrypted information. This project's main goal is to look at how these terrorists and hackers get our data by looking at the decrypted details. Why this study is more important? Many people's data is getting lost because of hackers and terrorists where people lose their money and lose the trust of government banks and securities. How hackers and terrorists get these information? They can easily hack by using people's Tax Id number or through revenue. This number is registered in peoples personal details which they have given to bank. So the hackers and terrorists can use this Tax ID and hack peoples account easily. It is not only about hacking and taking all the money from our bank accounts it is also about how our private life gets disturbed. This is an important topic that everyone needs to be aware of. Here government and securities have to play a vital role in how this can be solved. Understanding all of these terrorist and hacker methods can make our banking system and online payments safer. In this project, we are taking real-life individual data to show how all these details have been hacked in bad ways. This gives us a clear picture and an understanding. This project aims to provide useful information on how to protect our financial data even in critical situations. This project suggests that security and the government make online payments and bank details safer. This project finds more of the terrorists' and hackers' methods and finds out how they take our details.

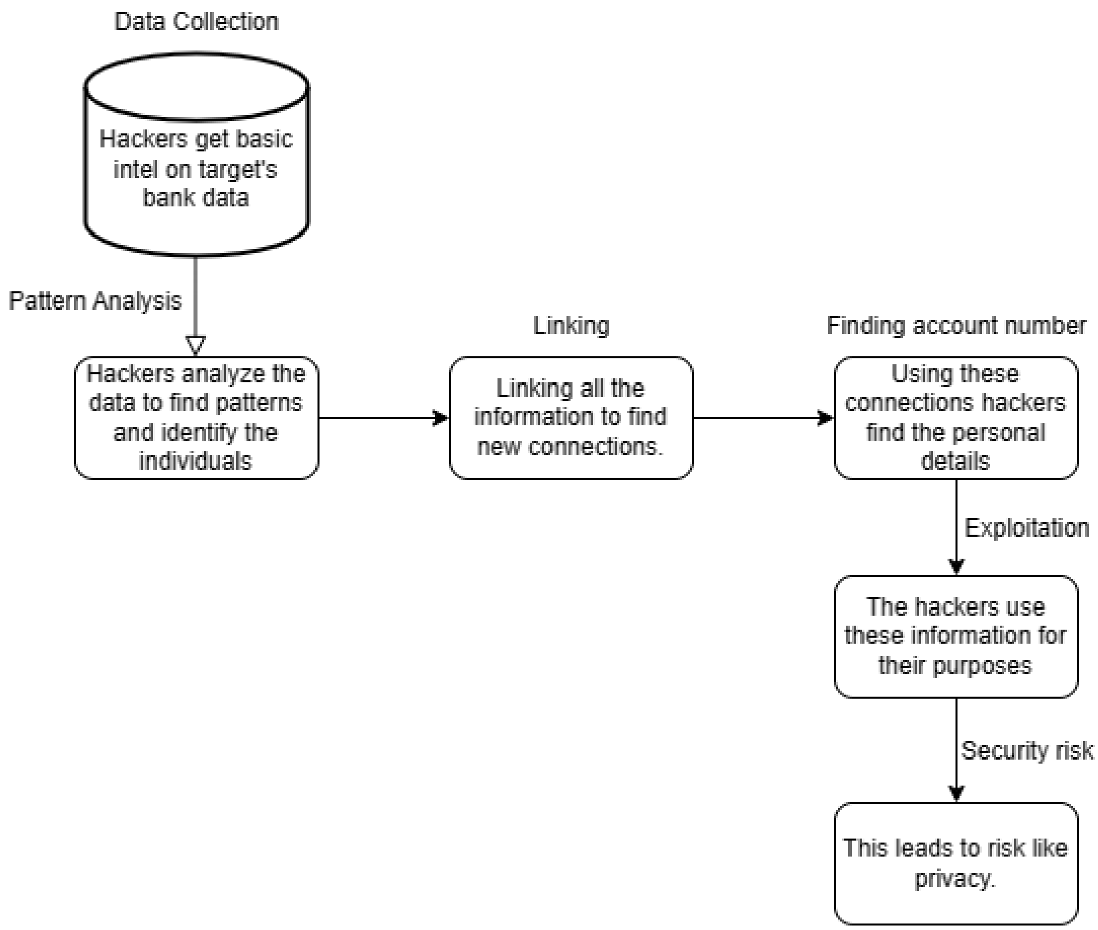

Figure 1:

2 Related Work

LSTM networks are distinguished by their unique ability to retain information over extended periods, which is crucial for identifying long-term patterns in data. They achieve this through a specialized component known as the LSTM cell structure. This structure is specifically designed to address the vanishing gradient problem commonly encountered in training RNNs with long data sequencesBkassiny (2022).

2.1 DETECTING FINANCIAL STATEMENT FRAUD:

Banks have a lot of data about their customers that keeps growing quickly.Craja et al. (2020) The big challenge in this study was to turn all this data into useful information and intelligence. Different research has been done to find patterns in how bank customers behave using various data mining techniques.

Nickerson et al. (2023)Machine learning, a part of Artificial Intelligence, is really useful in banking and finance. It helps banks spot fraud, helps managers decide who gets loans, and is used in things like chatbots for customer help, managing investments, and automated insurance.

As more people use their smartphones to make payments, they often don't lock their phones, which can lead to misuse or theft. Hilal et al. (2022)Banks and financial companies use different methods to prevent fraud and check who's using their services.

Network security has always been important since computers were created. Researchers use machine learning to improve intrusion detection systems. Abedin et al. (2023)They often use a specific dataset (KDDCUP-99) for training and testing these systems. Some studies have combined decision trees and neural networks to create smarter security systems.

A study by Ozbayoglu et al. (2020) looked at how deep learning is used in finance. They found it's mostly used for things like analyzing financial texts, automated trading, risk checking, understanding market sentiments, managing portfolios, and detecting fraud. Nazareth and Ramana Reddy (2023)They mainly used networks like LSTM, CNNs, and DMLP. Another study by Huang et al. (2020) also examined deep learning in finance, focusing on predicting things like exchange rates, stock markets, and oil prices, as well as banking risks and economic trends.

Studying how banks work is really important because banks play a big role in financial markets. Researchers are using more advanced tools like operational research (OR) and artificial intelligence (AI) for this. They're looking at things like making bank performance reviews fairer and predicting risks better, as well as improving how banks operate overall. These methods are becoming more popular in banking research.Nobanee et al. (2021)

2.2 AI IN FINANCIAL SECTOR

Yu et al. (2008)Synthetic data is like make-believe data that are made to look and act like real-world information. People use this kind of data when getting real data is too expensive or if there are worries about keeping people's personal information safe.

There's been a lot of research and studies done on how to spot unusual patterns or oddities in different areas, and this topic has been the focus of many review papers in recent years. These reviews cover a wide range of applications, strategies, and techniques that have significantly influenced research in various fields.Gajamannage et al. (2023)

Business intelligence started by pulling out important information from old data. Jiang et al. (2022)This was done by making special storage systems to handle and quickly analyze lots of data (Dicuonzo et al,2019).

Financial markets change a lot and are hard to predict. People use tools from areas like math and machine learning to try and forecast these markets accurately. Nuhiu and Aliu (2024)Recently, they started using a special kind of artificial intelligence called long short-term memory (LSTM) which has helped improve predictions. This study talks about using a special way of training two LSTMs to forecast financial markets in real time.

Investors use analyst reports to help decide if they should buy or sell stocks.Abbasi et al. (2021) These reports have been around for a long time and include predictions about earnings, advice on whether to buy, sell, or hold stocks, and other useful information. Most studies on these reports look at specific data like price targets and stock tips.

Artificial intelligence (AI) and blockchain are changing how banks work. These technologies make banking faster and safer. They also help create smart contracts on the blockchain, which improves digital transactions.Singh et al. (2023)

Modern communication systems, like the Internet of Things (IoT) and cell phone networks, create a lot of different kinds of data. Managing this data can be tough because it's so big and needs to be processed quickly and accurately. These networks are complicated, with things like moving devices and different types of connections. Lee et al. (2023)

Customer attrition, or churn, happens when customers stop doing business with a company.Kałużny (2019) In banking, this means when people close their bank accounts or stop using a bank's services. Banks need to understand why customers leave and try to stop it from happening.

The Expectation Confirmation Model (ECM) came from a theory in 1980 about how people's expectations match up with reality. It looks at four things: whether what people expect from a technology matches what it actually does, how useful they think the technology is, how happy they are with it, and if they plan to keep using it. León et al. (2020)

We chose artificial neural networks for recognizing patterns because they're really good at three things. First, they can learn complex patterns. Second, they don't need specific types of data to work well. Third, they're great at sorting or classifying things, even better than some of the latest traditional methods.TS and Shrinivasacharya (2021)

Recently,Chou et al. (2022) researchers have focused a lot on recurrent neural networks, especially Long Short-Term Memory (LSTM), because they're good at predicting complex, changing patterns over time. This paper reviews different types of LSTMs and how they predict time-based data. The best ones can remember information for both short and long periods and make accurate predictions.

Artificial intelligence, particularly machine learning, and deep learning, is changing finance. It's used for things like managing assets and giving stock advice. Banks aim to make marketing more precise to improve customer experience and keep them coming back. Robo-advisors, which give tailored financial advice, especially for stocks, are popular. Mirete-Ferrer et al. (2022)

For a long time, companies focused more on their products than their customers. But now, they see customers as their most important asset. It's key for businesses to understand what customers need and value long-term relationships with them. Companies use segmentation to identify and focus on their most important customers, especially as customer needs change quickly in today's digital and social media-driven world.Mosaddegh et al. (2021)

After the 2008 financial crisis, big banks were fined over 300 billion dollers by 2017. There were also a lot more rules to follow, so banks hired more people to deal with these regulations.Von Solms (2020) This increased their costs a lot, taking up about 10 percent of what they spend to run their business.

Finance involves making decisions about money and investments over time. This field often creates time-based data (time series) that can help predict future financial trends. These time series are useful Doumpos et al. (2023)because their patterns, like average values, don't change much over time. This data can help in making predictions about customers, companies, or whole industries. For example, you can predict a company's risk level compared to the market by analyzing different financial data sets together.

Banks play a big role in the economy by collecting deposits and investing them in smart ways. Experts like Schumpeterian and neo-Keynesian theorists say that when banks are good at directing money to useful projects, it really helps the economy grow. For banks to boost economic development, they need to know how well they're operating.Broby (2022)

Natural language processing (NLP) is a part of AI that helps understand text. It's popular now because of more digital data and tech advances. In finance, where lots of info like reports and contracts is in text, NLP is key to gaining insights.Bozyiğit and Kılınç (2022)

Using AI and Blockchain in governance is a big research area, focused on making things clearer. Alshamsi et al. (2021)Changing how governance works to make data more accessible and reduce differences in information among users is important.

3 Methodology

Procedure: In this project, we have bank transaction data where we could find the encrypted details like account number. This has more details of people's bank accounts. We have to see this information very carefully. This data has more hidden information. The main goal is to go through this information carefully and see if patterns can make us see the hidden information in people's bank accounts. This is done in an organized way so that we can understand this data and can come up with accurate solutions.

3.1 Data Preparation and Collection:

In this project, we collect all the details we need from our bank statement file. This has more information about different bank transactions. This includes the account numbers which are unique IDs of people's account details, transaction details that is how much money they deposit and withdraw, also we can able to see the balance amount of how much money is left in their account. The vital role here is to look for patterns. We want to see if these regular bank details can tell us any hidden information. In this what we found in the patterns can make us understand how this banking system works.

3.2 Data loading and exploration:

After collecting the data, we have to load this data to a dataFrame called Pandas. This will help us to keep the data organized and it is easier to work on more information. This will help us by changing all the raw data into a neat format where it will be easy to analyze. We can now start exploring this once we have our data in this dataframe. By looking at the data we can understand what this data is and what kind of information it is holding.

3.3 Tools and Techniques:

Pandas DataFrame: This tool is a very useful tool to work with our data. With this we can sort with data and we can look at specific informations or finding the patterns.

Data visualization tools: This is used for making charts and graphs. This will help to turn numbers and data into pictures and graphes. We can spot like how our amount is

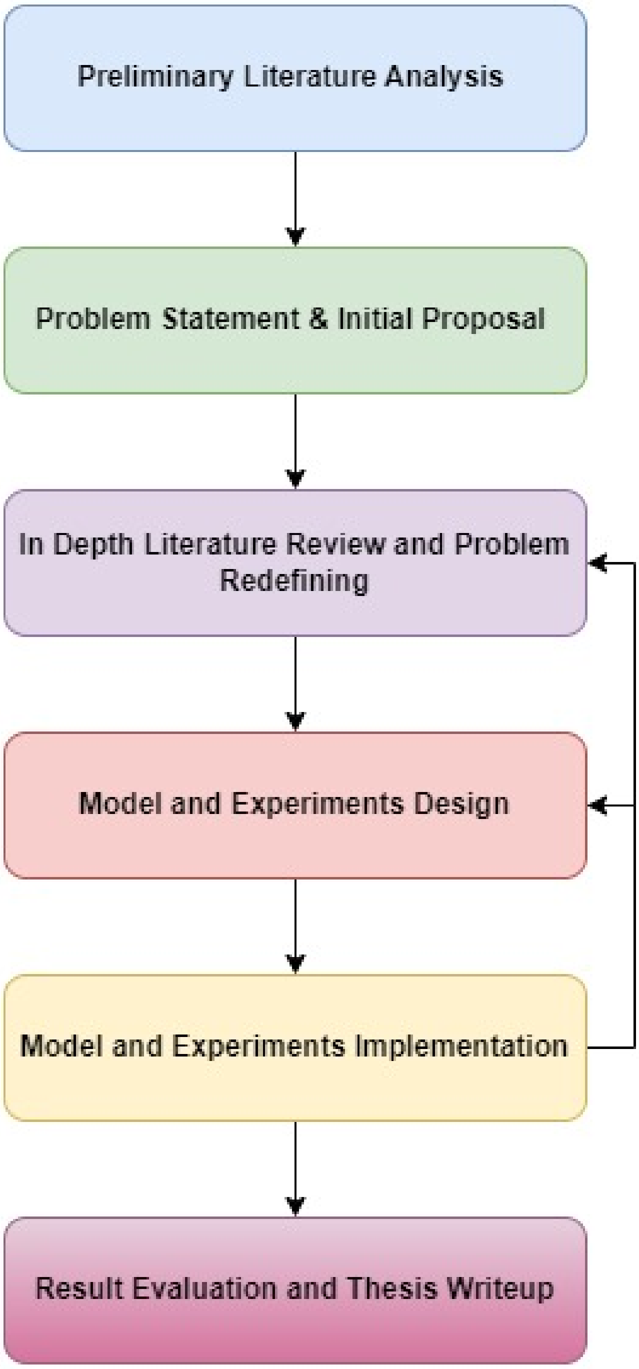

Figure 2: Research Process

going and down and also can able to notice any unusual activities or patterns. This will help us understand all the information by giving a clear picture.

3.4 Analyzing the data:

Exploratory data analysis: We connect with EDA which it analyze the data and find hidden patterns where anomalies things are found and it also it checks whether our hypotheses testing were right. This involves looking at the basic statistics of a data, and how often things happen in our data.

3.5 Pattern recognizing:

We focused on detecting were anything is happening unusual in the data. This leads to identify any sensitive account information. By finding these we can uncover hidden details which is in the regular transaction data.

3.6 Satistical methods:

Normalization techniques: This is used to work with numbers in a smarter way. This will help to adjust all the numbers in our data to a certain range. This will help to use the data in a better way.

Statistical testing: This ensures that the patterns we see is derived from data are statistically significant not due to any random things. Throughout this project, we were so careful about how each step was taken with attention in detail. First we had the raw data, we handle this data carefully by understanding and organizing. Then, analyzing the data helps looking for patterns, and at final we test the statistical check that the patterns we find in our data is actually true and not by any random chance.

4 Design Specification

This project involves a complex analysis of bank transaction data using a combination of data preprocessing techniques and Machine learning models.

4.1 DATA PREPARATION AND COLLECTION:

1. Loading the data: We load the bank transaction data which we have and this file has information that is, account numbers, transaction details, and balance amounts. We have used a tool called Pandas which is a Python library. We use this to handle our more organized and can handle efficiently.

2. Cleaning the data and preprocessing: In our bank data file we have a Transaction details column. It has textual data, so is cleaned by replacing the missing values with 'unknown'. This needs to make sure that there are no gaps in the data so it does not make any inaccurate predictions.

4.2 DATA NORMALIZATION AND TRANSFORMATION:

1. Scaling the numeric data: Using MinMaxScaler the 'BALANCE AMT' column is normalized. This scales the balance amount range of 0 to 1. This does not change the

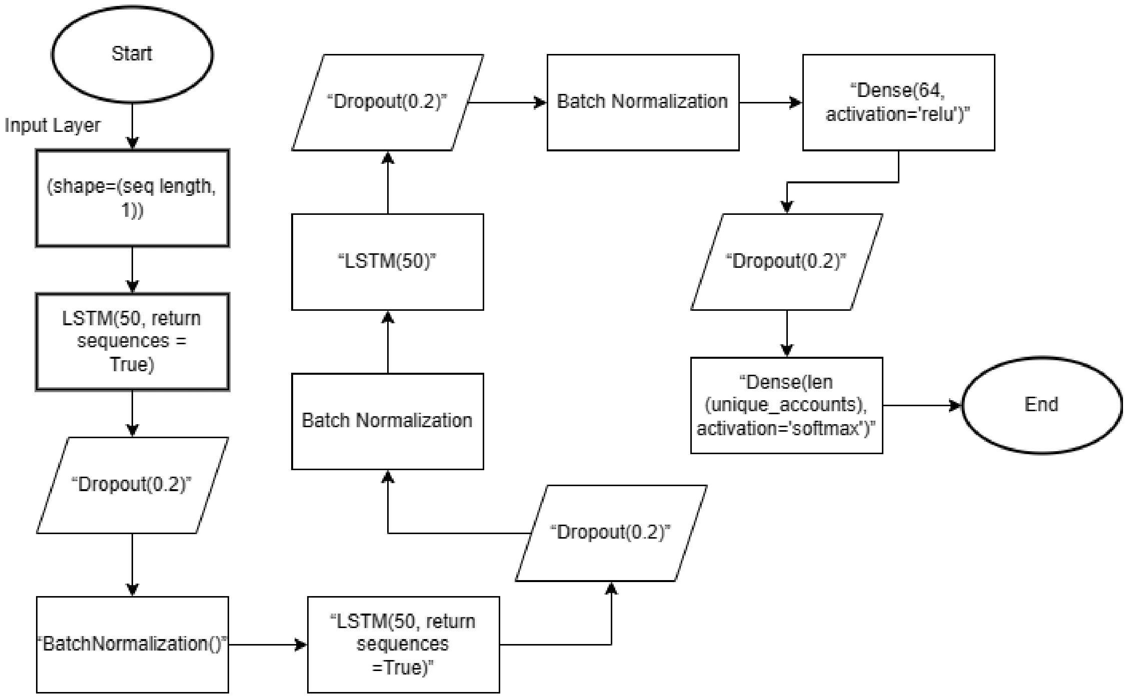

Figure 3: LSTM architecture figure

relative differences between the numbers, but it puts them all in a similar scale.

2. Textual data processing: For the 'TRANSACTION DETAILS' which are return words describing each transaction we use a process called Tokenization. In this, each unique word is given a specific number that the model can understand. For example, Withdraw can be 1 and deposit can be 0. This is translating a foreign language into numbers. There is another step like sentences have different lengths so the number sequences can be different too. so we 'pad' them adding extra zeros to the short ones to make them equal in length. To process the data efficiently for neural networks it is important to have inputs in uniform length.

3. Normalization: In our first LSTM model, we only looked at one kind of data, treating it as a pattern or signal, where the focus wasn't on how high or low the values were but on the pattern they formed. Because of this, using a method that adjusts all data points to a standard level (layer normalization) wasn't necessary. Instead, we made sure each group of data was consistent within itself through batch normalization, but this had little effect since we were only working with one type of data. For the second and third models, where we added transaction details to the mix, we approached it differently. We created two separate paths in our model: one for bank details and another for transaction details, which we then brought together. Each path was normalized on its own to manage the data's variability. This step was crucial, especially when combining different types of data, to ensure the model could handle data consistently, regardless of the varying patterns or sizes of the data batches. This approach, particularly using batch normalization separately for each path, prepares our model to identify patterns effectively, even in less-than-ideal conditions. It helps the model adjust to different scenarios, making our system more robust and adaptable in identifying critical patterns within the data.

Since RNN has exploding gradient problem, in LSTM the work is to reduce the exploding gradient problem. Basically LSTM is designed to reduce this problem. And also since we are doing batch normalization here, there is no chance for exploding gradient

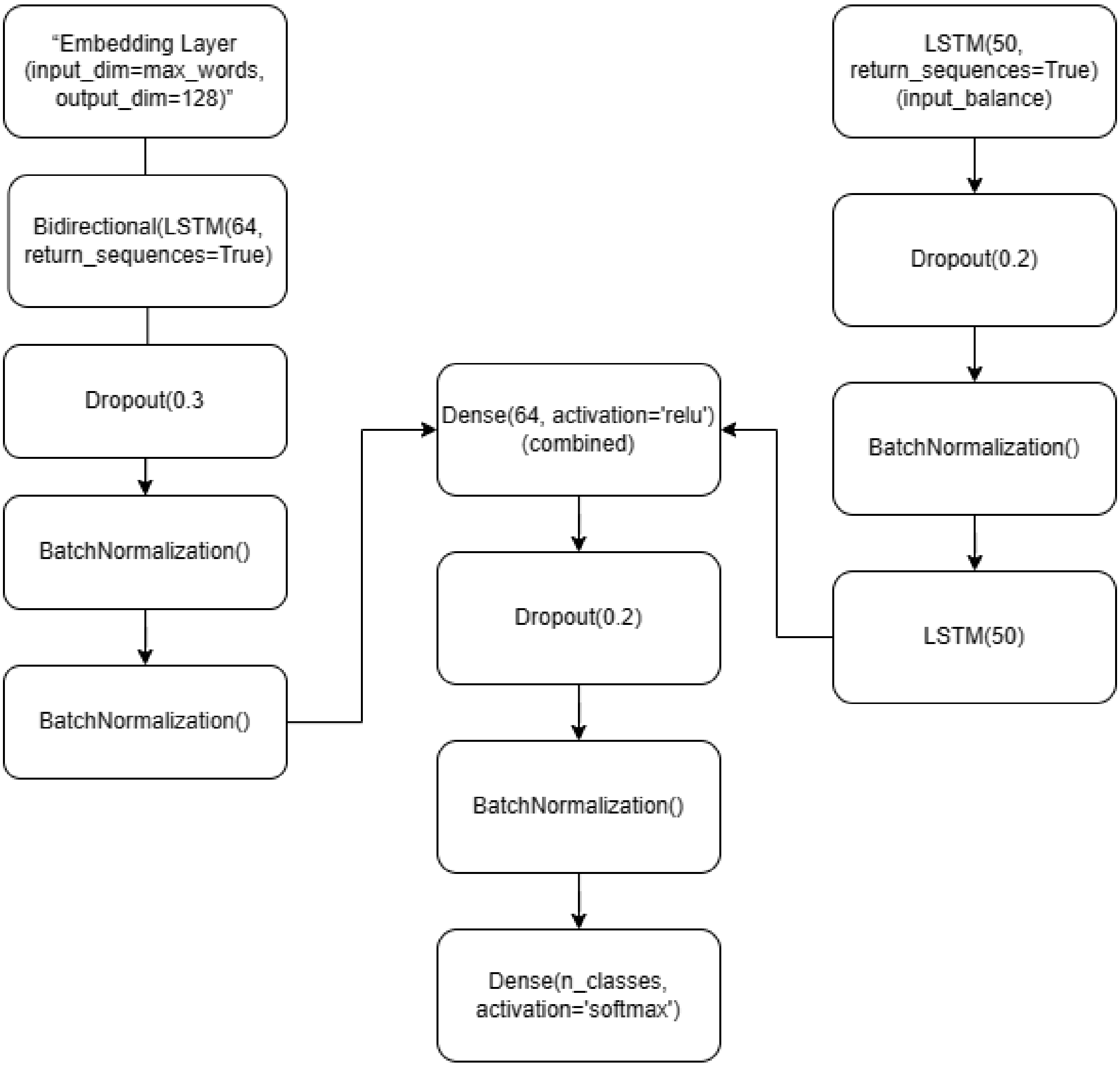

Figure 4: LSTM Bidirectional architecture figure

problem. And also we are using dropout layer. All the useless layers will dropout. Also vanishing gradient problem will also stop. Batch normalization will stop any further exploding gradient problem.

4.3 DATA ENCODING AND SPLITTING:

1. One-Hot Encoding: For this, we need to deal with the account numbers first. These account numbers are unique identifiers for each account, but the ML model cannot understand what they are. That is why we use a technique called One-Hot-Encoding. We have 10 different unique account numbers so the One-Hot encoding assigns each account number a unique pattern of 0's and 1's. This will make the ML model to understand easier so it recognizes and makes a difference between each account.

2. Train test Split: We will now split the data into two parts, training set and testing set. We use 80 percent of our data for training and the remaining 20 percent for testing. So, in our project, the model learns from the training set and then it gets tested on the testing set to see how it can predict accurately.

4.4 MODEL ARCHITECTURE AND TRAINING:

1. Building the Model: In our project, we have two separate pathways each designed to handle a different type of information, Balance amount, and Transaction details.

2. Balance Amount Processing: This balance amount in each transaction uses LSTM (Long short-term memory). This is good for understanding the data sequence that changes over time. This LSTM is good at noticing patterns in how the balance changes. This keeps track of all the money we have deposited or withdrawn over time and it can learn from sequences of these transactions and remember long-term transactions.

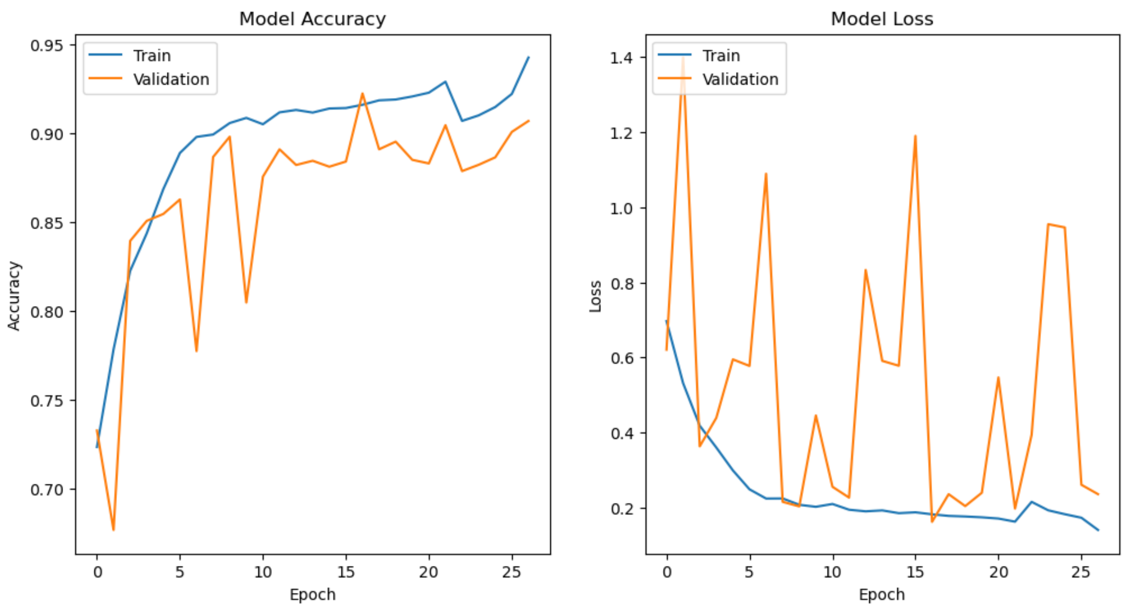

Figure 5: Training and Validation Accuracy and Loss

3. Transaction details processing: This uses the Embedding layer since all the details are written in words. This Embedding layer takes each word and keeps it in a space where similar types of words are close to this. This will help the model to understand the

meaning of all the words in the context of banking transactions. After the Embedding layer, we use LSTM layers. This will work on numbers that represent the words to understand the context.

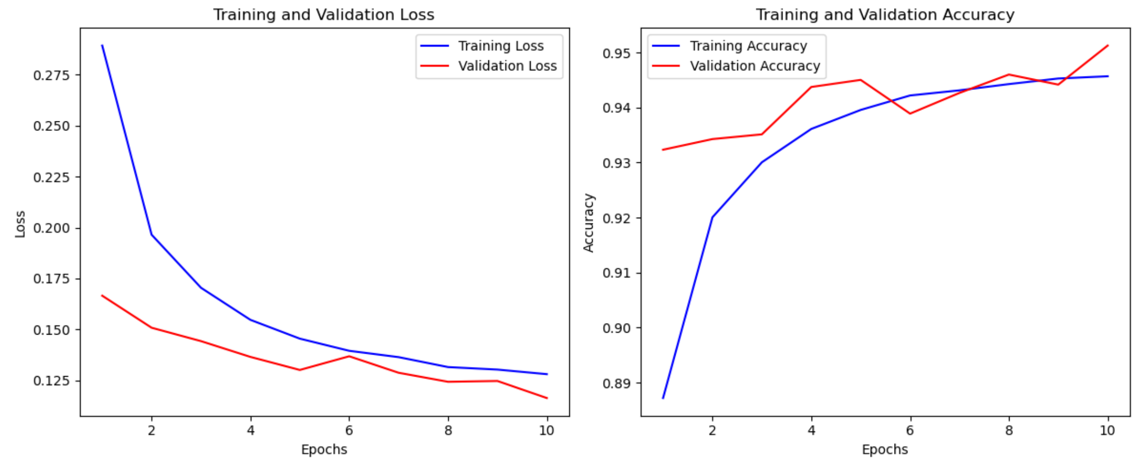

Figure 6: LSTM accuracy and loss

4. Combining data for prediction: The information from the balance amount and transaction details is concatenated. It is taking the information we got from the balance amount and transaction details and putting them together. By this, the model can look at what happened in the transaction and how much money was there. So, once it's combined the data goes through the Dense layers. This layer is a part of neural networks which makes the final decisions. This Dense layer uses the activation function called 'ReLU' and 'softmax'. Since this is a Multiclass classification task, the output should be in Probability. We have used 10 different classes. We have used Softmax activation function and TanH activation function. In LSTM, internally it has two activation functions which is Tanh activation function and the second has input gate, output gate and forgot gate. For all these gates sigmoid activation function is used. Inside LSTM these two activation function is there basically. So, the activation function we defined in final layer which is Softmax activation function. Here, 'ReLU' helps to make calculations efficiently, while 'Softmax' turns the final output into probabilities. Here if try to predict which account a transaction belongs to, 'Softmax' gives a probability score for each account.

5. Training the model: Now we prepare the model for training by compiling it. We use the 'Adam' optimizer to determine how the model learns and ensures it does efficiently. The 'categorical crosstropy' loss function tells the model how accurate its predictions are.

Now the model is trained using the training dataset where it learns with the examples we provide. It can make good predictions on the unseen data by learning and checking how well it is doing. Here we need to make sure that the model does not memorize the training data so we use the technique called Early stopping and ReduceLROnPlateau. Early stopping helps to safeguard that stops the training if the model is not improving on validation data. ReduceLROnPlateau - this technique is used to adjust the learning speed at which the model learns if the improvement is slowing down. So, this helps the model to learn more efficiently.

4.5 EVALUATION AND ANALYSIS:

Model Evaluation - After training the model, we test it using a separate set of data that has not been seen before which is called the test data set. Here we are specifically looking at how accurately the model can predict the right account number with the new balance amount and transaction details. This will help the model to understand more and ensure it is not only good with the data it was trained but also with the unseen data. In conclusion, this is a computer technique to make sense of bank data. We started by cleaning the data and organizing the data. We handled two types of data using LSTM which is a neural network. This model understands the sequence. We have converted the words into number formet so that the computer can understand.

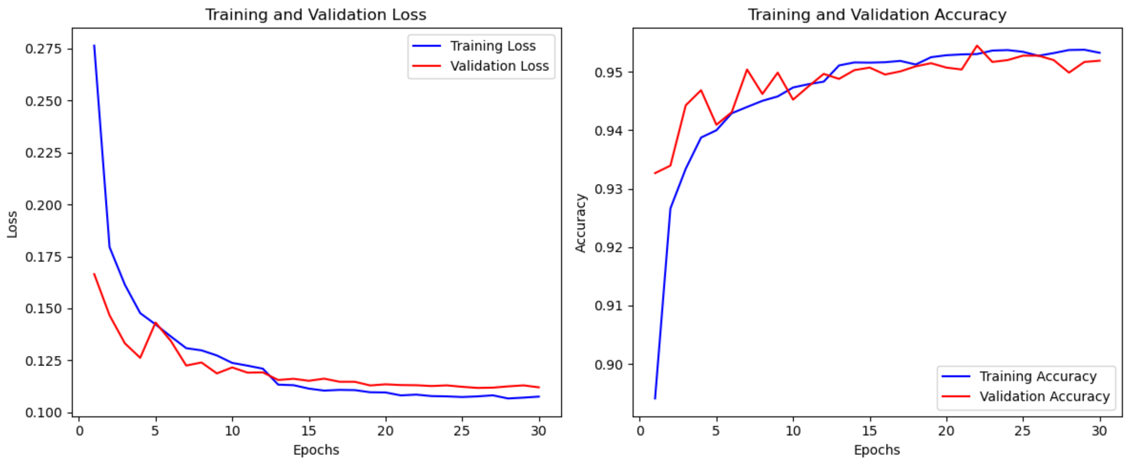

Figure 7: LSTM accuracy and loss

5 Implementation

This project uses a machine-learning techniques to understand and it guess what will happen with this complicated bank transactions. This model is very useful and can do a lot of work like better analyzing in finance data, find fraud before it happens, and make customer service better. It shows how using advanced computer methods can make a big difference in the banking world, especially for understanding complex information, keeping an eye out for any suspicious activities, and helping customers more effectively.

5.1 MODEL IMPLEMENTATION AND IMPLICATIONS:

1. Final implementation stage: This project finishes with the creation of an advanced computer model that learns from data. Here we used Python, a programming language, and some special tools like Pandas, TensorFlow, Keras, and Scikit-learn. Pandas helped to arrange and work with the data, while TensorFlow and Keras were used to build the part of this model that can learn and make decisions, known as a neural network. Scikit-learn was used to get in the data ready for the model. This model is made up of two main parts: one that deals with numbers (like how much money is in an account) and another that handles words (like what the transactions are about). This setup allows your model to understand and learn from both the numbers and descriptions in bank transactions.

2. Data processing and transformation: This method begins by changing the original bank data into a form that's easier for the computer to learn from. This includes making all the number data (like account balances) fit into a standard range and turning words (like transaction descriptions) into numbers. By doing this, our computer model can better understand and use this information. This step is really important because it helps the model deal with lots of different kinds of data, which is something banks often have to do. It's like translating a foreign language into your own language so you can understand and use the information more easily. This makes it possible for the model to analyze big and varied sets of banking data effectively.

3. Advanced neural network application: Using LSTM networks, which stand for Long Short-Term Memory, is a big step into the world of deep learning. These LSTMs are really good at understanding data that comes in a sequence or over time, like bank transactions. They help figure out patterns in these transactions and spot anything unusual happening across different times. Also, our model uses something called an embedding layer when it works with text data. This layer helps the model really get the meaning behind the words used in transaction descriptions. It's like adding an extra level of understanding to what each transaction is really about. Together, these features make your model smart at analyzing banking data, not just looking at the numbers but also understanding the stories behind them.

4. Predictive Modelling and Analysis: This model is really useful for banks and financial companies. It can guess how accounts will act, find strange transactions that might be fraud, and learn how customers like to spend their money. In real-world use, this means banks can make their security better, group customers in smarter ways, and create marketing plans that hit the mark more accurately. It's like having a smart assistant that not only keeps an eye on accounts for anything odd but also helps banks understand their customers better and reach out to them in more effective ways.

5. Training and Validation: By dividing the data into parts for training and testing, and using methods like stopping early and slowing down the learning speed, the model is really well-trained and checked. This makes sure it works well and accurately when used for real tasks. This is super important for banks and financial places in managing risks and making smart decisions. It gives them a strong, data-based way to handle important jobs, like making sure they're making safe and sound choices based on what the data tells them.

6. Tuning: In our LSTM neural network, first is number of lstm units in each layer. And, in dropout there is percentage of dropout. In normal neural networks in dense layer there we define number of neurons, that has activation function and dropout. So this is a multi class classification. Here in learning rate we have used a call back function and reduce learning rate on plateau. In gradient desent plateau is like plain surface. Usually it will be very low to the final. So we are using minimum learning rate that is 0.0001 that is the minimum learning rate that we are using. In other, whatever adam optimizer learning rate is there the same is there. Only in plateaus we are using minimum rate. So what is the advantage is when the decent approaches to the minimum, the steps are very small so that it doesn't over fit the data. We have defined 50 lstm units. We have kept window size as 100. We have kept 25 units, 35 units and 50 units. In 50 units we find the better results. If we increase the units for training it is getting delayed. Also RAM utilization is also increasing. Considering this, for this laptop the maximum possible units is 50 units. For dropout, for the first two models we used 20%. So 20 percent of the data will be loss. If we keep 30, the accuracy is getting low. So optimally keeping 20% is

the best. Next parameter we tuned is batch size, we took batch size as 32 so considering RAM usage this took batch size as 32. If the batch size increases RAM usage is getting high and system might crash since we only 8GB RAM. Also we used early stopping, we are using epochs. Nearly we are using 200 epochs. The accuracy might increase or might drop. Early stopping we kept patience as 10. If accuracy drops more than 10 then the model will stop and restore the best accuracy that was got before.

7. Model Evaluation: After the training, when the model is tested with new data it hasn't seen before, it shows us how well it can apply what it learned to real-world situations. This step is really important to see if the model is useful for working with actual banking data that it hasn't come across in training. If the model does well in this test, it means it's very good at understanding and working through banking transactions. This makes it a strong and reliable tool for analyzing financial data, helping banks and financial institutions make sense of their numbers and information.

8. Impacts on bank operations: Using this model could change the way banks work in many ways. It can make it easier to spot fraud, give helpful information to make customer service better, and make the whole banking operation run more smoothly. The model does a lot of different and important things. Also, it shows a great example of how to mix AI and machine learning into the usual way banks do things. This could lead to newer and smarter ways of banking that rely more on data. It's like giving banks a new set of tools that help them work smarter, understand their customers better, and stay ahead of problems like fraud.

9. Future development: This model lays the groundwork for even better features in the future, like watching transactions as they happen, using more varied types of data, and applying it to different areas of finance. There's also room to make it even better by combining it with new tech like blockchain. This could make things more secure and clear. It's a starting point that could lead to a lot of exciting improvements and new ways to use the model, making banking smarter, safer, and more open to exploring new technologies and ideas.

10. Ethical considerations and compliance: Using this model means we have to be careful about customer privacy and make sure the AI isn't biased. It's important to follow rules about how to use and protect people's data in banking, so everything is done right and legally.

11. Practical applications in real-world: The way this model works can be used not just in banking, but also in businesses like online shopping, phone services, and healthcare. It shows how AI and learning computers can help solve real-world problems, not just in theory but in actual practice.

6 Evaluation

Evaluating our project is key to seeing how well the AI model works for looking at bank transactions. This part checks how good the results are and what they mean for both study and real-world use.

6.1 MODEL ACCURACY PERFORMANCE:

To see how well the model worked, we used something called categorical cross-entropy. This is a way to check how accurate the model is, especially for tasks where it has to put things into categories. It looks at how close the model's guesses are to the actual answers. For this project, we looked at how well the model could guess the right bank account numbers based on the transaction data. If the cross-entropy number is small, it means the model did a really good job at picking the right account numbers. So, a lower number here means the model is more accurate at figuring out which transactions belong to which accounts.

6.2 SIGNIFICANCE OF FINDINGS:

The model showed a good high accuracy and low categorical entropy score. This means it's great at understanding and making sense of complicated bank transactions. The fact that it could correctly figure out account numbers just from looking at how transactions happen proves that the way you built and trained the model works well. It also shows just how powerful AI can be in pulling out important information from big sets of data. So, your model is accurate and a strong example of how AI can help us get valuable knowledge from complex information.

6.3 IMPLICATIONS:

1. Academic Perspective: From a study and research perspective, this project adds a lot to what we know about using neural networks, a kind of AI, for looking at financial data. It shows that LSTM networks, a special kind of AI, are good at dealing with both numbers and words when they're prepared in the right way. This is a big step forward in learning more about machine learning and data science. It's like discovering a new, effective way of using smart technology to understand and work with the kind of complex information that we find in finance.

2. Practical perspective: In real-world use, the model's skill in figuring out account numbers can be both helpful and risky. On one hand, it shows how AI can be really useful in banks for things like finding fraud and understanding how customers act. This means banks can use AI to get smarter about spotting problems and knowing what their customers want. On the other hand, there's a downside because it might be misused. The fact that even a small model can get sensitive details like account numbers points to a security weakness. This could be a problem if bad people, like hackers or terrorists, use AI in the wrong way to get private information that they shouldn't. It's a warning that while AI can do great things, it also needs to be used carefully and protected to make sure it doesn't fall into the wrong hands and cause harm.

3. Call for enhanced security: The results really highlight how important it is for banks to have stronger security. Banks and the groups that oversee them need to really get how AI and machine learning work. They should know not just the good things these technologies can do but also the dangers they might bring. It's really important to create better, tougher security rules and to use more advanced AI tools for protection. This way, banks can defend themselves against the kind of weaknesses that might be misused. In simple terms, it's about making sure banks are super safe in a world where AI is everywhere.

This project shows that AI can be both amazing and risky for finance. It can improve banking and help customers, but there's a chance it could be misused. This means banks must use AI wisely and have strong security to keep it safe and used right.

6.4 Discussion

In this project, we ran a bunch of tests, called 'N experiments', to see how well a machine learning model worked with bank transaction data. These tests were set up to check if the model could correctly pick out account numbers and make sense of the patterns in how transactions happen. We were testing to see if this computer model was smart enough to understand and analyze the details of banking transactions, like figuring out which transactions belong to which accounts and noticing any regular patterns in how these transactions take place.

1. Critical analysis of experiments:

Experiment design and execution: The experiments were well-planned, focusing on an important part of how banks work. But they mainly looked at how technically good the AI model was, maybe not considering the bigger picture as much. A big issue was that the data used for training and testing the model wasn't very diverse. It was just one type of data, which might not show all the different and complex situations you find in real banking.

2. Performance of the AI Model:

The model, using something called an LSTM network, was good at dealing with data that comes in a series, like bank transactions. Understanding the order and connection of transactions is essential for analyzing them, and the model did this well. However, when it came to dealing with the words and details in transactions, the model wasn't as strong. Banking transactions can have a lot of different kinds of descriptions, and the model struggled with this variety. This weakness could be a problem when the model is used in real-life situations where transaction details can be very different from one another.

FUTURE IMPROVEMENTS:

In future improvements for the AI model, it's crucial to include a wider variety of banking transaction data to test the model's adaptability across different banking scenarios. Enhancing the model's ability to understand transaction descriptions through more advanced natural language processing techniques is also important. Additionally, adding a feature to detect anomalies would be valuable, particularly for identifying fraudulent transactions in banking. Equally important is considering the user experience and how bank employees will interact with the AI system, ensuring that the model integrates well into the daily operations of a bank. These improvements aim to make the model more versatile, accurate, and user-friendly, enhancing its practical utility in real-world banking applications.

7 Conclusion and Future Work

CONCLUSION AND FUTURE WORK: The main research goal was to look at how using AI to do jobs usually done by people affects data privacy and security in government work. This is really important today as AI is being used more and more in different areas, like in government tasks. In this project, we made and tested a machine learning model that looks closely at detailed bank transactions. This model was like a small example of how AI can be used in government work. You showed that AI, using smart methods like LSTM networks, is really promising for making data analysis tasks, usually done by people, more efficient and thorough. This study showes two sides of using AI in government. On one side, AI is great for doing complex jobs automatically, making things faster and finding important details that people might miss. But on the other side, Here, we found that using AI could lead to worries about keeping data private and the wrong use of AI. These points are extra important because government agencies handle very sensitive data. What makes this research stand out is how it looks at both the good and the bad sides of AI in government. It gives advice to both policymakers and tech experts. One thing to remember, though, is that this research mainly looked at financial data, so it might not cover all the ways AI can be used in other government areas. Also, AI is changing fast, so what we know about it keeps changing too.

1. Implications and future directions:

This research has a lot of important effects. For people working in government, it shows how crucial it is to protect data and use AI in a way that's right and fair. For researchers and scholars, it lays a groundwork for more study into how AI can help in government tasks. It also brings up important questions about how to use advanced technology responsibly and ethically. This research work points out the need for both strong data safety and thinking carefully about the right way to use AI in government roles.

2. Commercialization potential:

This project has the potential to turn into real products. Software companies could use this AI model to create tools for government agencies. There's also a chance for businesses that advise on using AI to make the government work better while keeping data safe and private. In short, this work is not just important for academic studies about AI in government but also shows a way to use AI responsibly and securely in real-life government tasks. It opens doors for new ideas and business chances, emphasizing the importance of using AI carefully in government.

References

Abbasi, M., Shahraki, A. and Taherkordi, A. (2021). Deep learning for network traffic monitoring and analysis (ntma): A survey, *Computer Communications* **170**: 19–41.
URL: *https://www.sciencedirect.com/science/article/pii/S0140366421000426*

Abedin, M. Z., Hajek, P., Sharif, T., Satu, M. S. and Khan, M. I. (2023). Modelling bank customer behaviour using feature engineering and classification techniques, *Research in International Business and Finance* **65**: 101913.
URL: *https://www.sciencedirect.com/science/article/pii/S0275531923000399*

Alshamsi, M., Salloum, S., Alshurideh, M. and Abdallah, S. (2021). *Artificial Intelligence and Blockchain for Transparency in Governance*, pp. 219–230.

Bkassiny, M. (2022). A deep learning-based signal classification approach for spectrum sensing using long short-term memory (lstm) networks.

Bozyiğit, F. and Kılınç, D. (2022). *Practices of Natural Language Processing in the Finance Sector*, Springer Nature Singapore, Singapore, pp. 157–170.
URL: *https://doi.org/10.1007/978-981-16-8997-0*$_9$

Broby, D. (2022). The use of predictive analytics in finance, *The Journal of Finance and Data Science* **8**: 145–161.
URL: *https://www.sciencedirect.com/science/article/pii/S2405918822000071*

Chou, Y.-C., Chen, C.-T. and Huang, S.-H. (2022). Modeling behavior sequence for personalized fund recommendation with graphical deep collaborative filtering, *Expert Systems with Applications* **192**: 116311.
URL: *https://www.sciencedirect.com/science/article/pii/S0957417421016122*

Craja, P., Kim, A. and Lessmann, S. (2020). Deep learning for detecting financial statement fraud, *Decision Support Systems* **139**: 113421.
URL: *https://www.sciencedirect.com/science/article/pii/S0167923620301767*

Doumpos, M., Zopounidis, C., Gounopoulos, D., Platanakis, E. and Zhang, W. (2023). Operational research and artificial intelligence methods in banking, *European Journal of Operational Research* **306**(1): 1–16.
URL: *https://www.sciencedirect.com/science/article/pii/S037722172200337X*

Gajamannage, K., Park, Y. and Jayathilake, D. I. (2023). Real-time forecasting of time series in financial markets using sequentially trained dual-lstms, *Expert Systems with Applications* **223**: 119879.
URL: *https://www.sciencedirect.com/science/article/pii/S0957417423003809*

Hilal, W., Gadsden, S. A. and Yawney, J. (2022). Financial fraud: A review of anomaly detection techniques and recent advances, *Expert Systems with Applications* **193**: 116429.
URL: *https://www.sciencedirect.com/science/article/pii/S0957417421017164*

Jiang, X.-F., Xiong, L., Cen, T., Bai, L., Zhao, N., Zhang, J., Zheng, C.-J. and Jiang, T.-Y. (2022). Analyst sentiment and earning forecast bias in financial markets, *Physica A: Statistical Mechanics and its Applications* **589**: 126601.
URL: *https://www.sciencedirect.com/science/article/pii/S0378437121008669*

Kałużny, P. (2019). Behavioral biometrics in mobile banking and payment applications, *in* W. Abramowicz and A. Paschke (eds), *Business Information Systems Workshops*, Springer International Publishing, Cham, pp. 646–658.

Lee, J. C., Tang, Y. and Jiang, S. (2023). Understanding continuance intention of artificial intelligence (AI)-enabled mobile banking applications: an extension of AI characteristics to an expectation confirmation model, *Humanities and Social Sciences Communications* **10**(1).
URL: *https://doi.org/10.1057/s41599-023-01845-1*

León, C., Barucca, P., Acero, O., Gage, G. and Ortega, F. (2020). Pattern recognition of financial institutions' payment behavior, *Latin American Journal of Central Banking* **1**(1): 100011.
URL: *https://www.sciencedirect.com/science/article/pii/S2666143820300119*

Mirete-Ferrer, P., Garcia-Garcia, A., Baixauli-Soler, J. and Prats, M. (2022). A review on machine learning for asset management, *Risks* **10**: 84.

Mosaddegh, A., Albadvi, A., Sepehri, M. M. and Teimourpour, B. (2021). Dynamics of customer segments: A predictor of customer lifetime value, *Expert Systems with Applications* **172**: 114606.
URL: *https://www.sciencedirect.com/science/article/pii/S0957417421000476*

Nazareth, N. and Ramana Reddy, Y. V. (2023). Financial applications of machine learning: A literature review, *Expert Systems with Applications* **219**: 119640.
URL: *https://www.sciencedirect.com/science/article/pii/S0957417423001410*

Nickerson, K., Tricco, T., Kolokolova, A., Shoeleh, F., Robertson, C., Hawkin, J. and Hu, T. (2023). Banksformer: A deep generative model for synthetic transaction sequences, *in* M.-R. Amini, S. Canu, A. Fischer, T. Guns, P. Kralj Novak and G. Tsoumakas (eds), *Machine Learning and Knowledge Discovery in Databases*, Springer Nature Switzerland, Cham, pp. 121–136.

Nobanee, H., Dilshad, M. N., Dhanhani, M. A., Neyadi, M. A., Qubaisi, S. A. and Shamsi, S. A. (2021). Big data applications the banking sector: A bibliometric analysis approach, *SAGE Open* **11**(4): 21582440211067234.
URL: *https://doi.org/10.1177/21582440211067234*

Nuhiu, A. and Aliu, F. (2024). *The Benefits of Combining AI and Blockchain in Enhancing Decision-Making in Banking Industry*, Springer International Publishing, Cham, pp. 305–326.
URL: *https://doi.org/10.1007/978-3-031-35751-0*$_2$2

Singh, P. P., Anik, F. I., Senapati, R., Sinha, A., Sakib, N. and Hossain, E. (2023). Investigating customer churn in banking: A machine learning approach and visualization app for data science and management, *Data Science and Management* .
URL: *https://www.sciencedirect.com/science/article/pii/S2666764923000401*

TS, P. and Shrinivasacharya, P. (2021). Evaluating neural networks using bi-directional lstm for network ids (intrusion detection systems) in cyber security, *Global Transitions Proceedings* **2**(2): 448–454. International Conference on Computing System and its Applications (ICCSA- 2021).
URL: *https://www.sciencedirect.com/science/article/pii/S2666285X21000455*

Von Solms, J. (2020). Integrating Regulatory Technology (RegTech) into the digital transformation of a bank Treasury, *Journal of Banking Regulation* **22**(2): 152–168.
URL: *https://doi.org/10.1057/s41261-020-00134-0*

Yu, L., Wang, S. and Lai, K. K. (2008). Credit risk assessment with a multistage neural network ensemble learning approach, *Expert Systems with Applications* **34**(2): 1434–1444.
URL: *https://www.sciencedirect.com/science/article/pii/S0957417407000206*