Bank Loan Fraud Detection Using ML

A PROJECT REPORT

Submitted By

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Under the Supervision of
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Submitted to

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CERTIFICATE

Certified that **Rudra Pratap Singh (Enrollment No. 20029014005792)** have carried out the project work having "**Bank Loan Fraud Detection Using ML**" for Master of Computer Applications from Dr. A.P.J. Abdul Kalam Technical University (AKTU) (formerly UPTU), Technical University, Lucknow under my supervision. The project report embodies original work, and studies are carried out by the student himself / herself and the contents of the project report do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

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This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

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ABSTRACT

When someone borrows some money from someone or some organization, in financial term it is known as loan .Distribution of the loans is the core business part of almost every banks. The main portion the bank's assets I s directly came from the profit earned from the loans distributed by the banks. The prime objective in banking environment is to invest their assets in safe hands where it is. Today many banks/financial companies approve loan after a regress process of verification and validation but still there is no surety whether the chosen applicant is the deserving right applicant out of all applicants. Through this system we can predict whether that particular applicant is safe or not and the whole process of validation of features is automated by machine learning technique. The disadvantage of this model is that it emphasizes different weights to each factor but in real life sometime loan can be approved on the basis of single strong factor only, which is not possible through this system.

The objective of the problem is to pick out which customer will be able to pay the debt and which customer is likely will not be able to pay the debts. Clearly, we have to create a classification model here. We have to use algorithms like logistic regression, decision tree or random forest. We need to create a model that is accurate and the error percentage should be less. The main objective of this project is to predict whether assigning the loan to particular person will be safe or not. ... In this paper we are predict the loan data by using some machine learning algorithms they are classification, logic regression, Decision Tree and gradient boosting.

A classification model is run on data attempting to classify whether the person or client is eligible for get loan from any bank with good accuracy of statement.

Keywords: Objective, Applicant, Classification.

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Rudra Pratap Singhs

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CHAPTER 1

INTRODUCTION

OVERVIEW

When someone borrows some money from someone or some organization, in financial term it is known as loan. Distribution of the loans is the core business part of almost every banks. The main portion the bank's assets I s directly came from the profit earned from the loans distributed by the banks. The prime objective in banking environment is to invest their assets in safe hands where it is. Today many banks/financial companies approve loan after a regress process of verification and validation but still there is no surety whether the chosen applicant is the deserving right applicant out of all applicants. Through this system we can predict whether that particular applicant is safe or not and the whole process of validation of features is automated by machine learning technique. The disadvantage of this model is that it emphasizes different weights to each factor but in real life sometime loan can be approved on the basis of single strong factor only, which is not possible through this system.

1.1 History of Machine Learning

A brief history of Machine Learning is discussed as follows:

Machine learning (ML) is an important tool for the goal of leveraging technologies around artificial intelligence. Because of its learning and decision-making abilities, machine learning is often referred to as AI, though, in reality, it is a subdivision of AI.

Until the late 1970s, it was a part of AI's evolution. Then, it branched off to evolve on its own. Machine learning has become a very important response tool for cloud computing and eCommerce, and is being used in a variety of cutting edge technologies. Machine learning is a necessary aspect of modern business and research for many organizations today. It uses algorithms and neural network models to assist computer systems in progressively improving their performance. Machine learning algorithms automatically build a mathematical model using sample data – also known as "training data" – to make decisions without being specifically programmed to make those decisions.

Machine Learning is, in part, based on a model of brain cell interaction. The model was created in 1949 by Donald Hebb in a book titled The Organization of Behaviour (PDF). The book presents Hebb's theories on neuron excitement and communication between neurons. Hebb wrote, "When one cell repeatedly assists in firing another, the axon of the first cell develops synaptic knobs (or enlarges them if they already exist) in contact with the soma of the second cell." Translating Hebb's concepts to artificial neural networks and artificial neurons, his model can be described as a way of altering the relationships between artificial neurons (also referred to as nodes) and the changes to individual neurons. The relationship between two neurons/nodes strengthens if the two neurons/nodes are activated at the same time and weakens if they are activated separately. The word "weight" is used to describe these relationships, and nodes/neurons tending to be both positive or both negative are described as having strong positive weights. Those nodes tending to have opposite weights develop strong negative weights.

- In **1943**, Machine learning history starts with the first mathematical model of neural networks presented in the scientific paper "A logical calculus of the ideas immanent in nervous activity" by Walter Pitts and Warren McCulloch.

- **In 1949** The book "The Organization of Behaviour" by Donald Hebb is published. This book has theories on how behavior relates to neural networks and brain

activity and is about to become one of the monumental pillars of machine learning development.

- **In 1950,** Arthur Samuel, a pioneer in system studying, created a software for playing championship-degree pc checkers. in preference to learning every and every feasible path, the sport used alpha-beta pruning that measured probabilities of triumphing. additionally, Samuel applied a minimax set of rules (which continues to be extensively used for video games nowadays) of finding the superior pass, assuming that the opponent is also gambling optimally. He additionally designed mechanisms for his software to constantly improve, for example, via remembering previous checker moves and comparing them with chances of winning. Arthur Samuel is the primary man or woman to provide you with and popularize the time period "device getting to know".

- **In 1965,** Ukrainian-born soviet scientists Alexey (Oleksii) Ivakhnenko and Valentin Lapa have advanced hierarchical representation of neural community that uses polynomial activation feature and are trained the usage of group technique of information managing (GMDH). it's far taken into consideration because the first ever multi-layer perceptron and Ivakhnenko is frequently considered as the daddy of deep studying..

- **In 1990,** Paper “The Strength of Weak Learnability” by Robert Schapire and Yoav Freund introduce boosting for machine learning. Boosting is an algorithm which aims to enhance predicting power of an AI model. Instead of using a single strong model, it generates many weak models and converts them into strong ones by combining their predictions (usually, using averages or voting).

- **In 1995,** Random decision forests are introduced in a paper published by Tin Kam Ho. This algorithm creates and merges multiple AI decisions into a "forest". When relying on multiple different decision trees, the model significantly improves in its accuracy and decision-making.

- **In 1997**, Video Rewrite application — first "deepfake" software program is developed through Christoph Bregler, Michele Covell and Malcolm Slaney.
  IBM chess laptop, Deep Blue, beats international champion Garry Kasparov in chess. on the time this achievement turned into visible as a evidence of machines catching as much as human intelligence.
- **In 2000,** First mention of the term "deep mastering" with the aid of a Ukrainian-born neural networks researcher Igor Aizenberg within the context of Boolean threshold neurons.
- **In 2011,** Having an intensive gadget studying heritage, Google's X Lab crew has developed an artificial intelligence set of rules Google mind, which later in 2012 became famously desirable at photo processing, being capable of pick out cats in photographs.
- **In 2014,** Facebook investigate group creates DeepFace, a profound inclining facial acknowledgment framework — nine-layer neural arrange prepared on 4 million pictures of Facebook clients. This AI is able to spot human faces in pictures with the same exactness as people do (around 97.35%) Figure(1.1) shows example of Deep Learning.

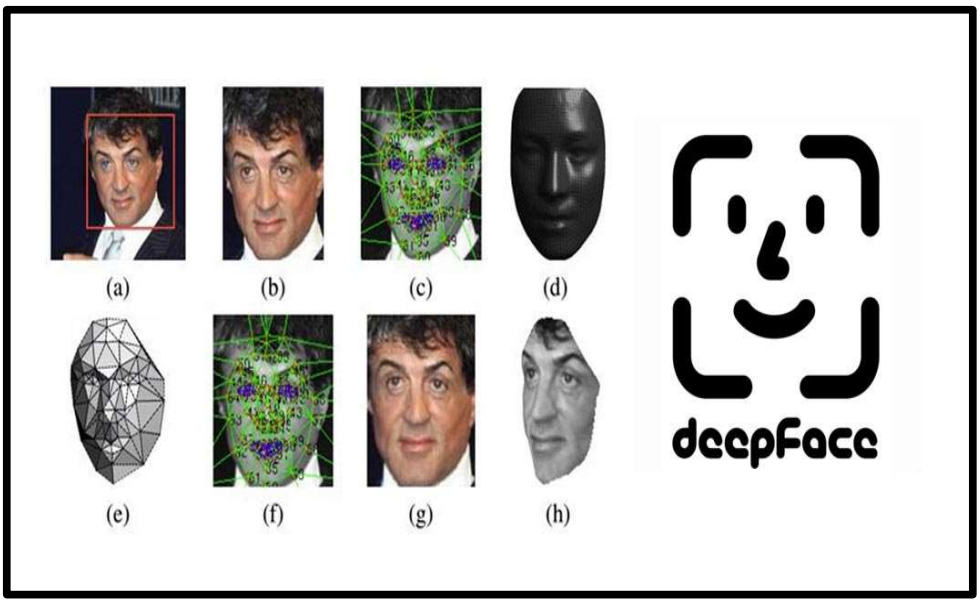


Figure 1.1: Example deep Learning

- **In 2016,** A gather of researchers presents Face2Face amid the Conference on Computer Vision and Design Acknowledgment. Its rationale and calculations are the premise of lion's share of today's "deepfake" computer program.
- **In 2017,** Waymo begins testing independent cars within the US with reinforcement drivers as it were at the back of the car. Afterward the same year they introduce completely independent taxis within the city of Phoenix (Figure 1.2).

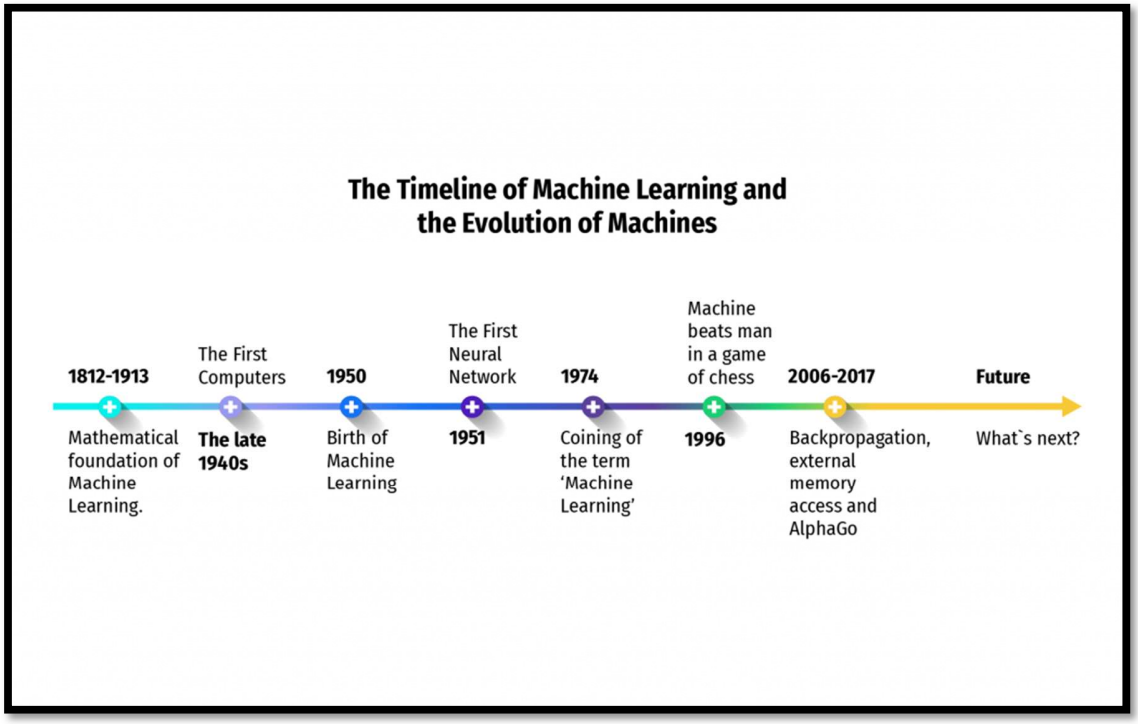


Figure 1.2: Brief History of Machine Learning

1.2 Machine Learning Algorithms

Machine Learning calculations are the programs that can learn the covered-up designs from the information, anticipate the yield, and progress the execution from encounters on their possess. Distinctive calculations can be utilized in machine learning for diverse assignments, such as basic straight relapse that can be utilized for expectation issues like stock advertise forecast, and the KNN calculation can be utilized for classification issues.

Machine Learning Calculations are characterized as the calculations that are utilized for preparing the models, in machine learning it is partition into three distinctive sorts, i.e., Administered Learning(in this dataset are labeled and Relapse and Classification procedures are utilized), Unsupervised Learning (in this dataset are not labeled and methods

like Dimensionality diminishment and Clustering are utilized) and Fortification Learning (calculation in which demonstrate learn from its each activity) for the improvement of machine learning arrangement for applications such as Client Maintenance, Picture Classification, Expertise Procurement, Client Division, Amusement AI, Climate estimating, Advertise Determining, Diagnostics, etc.

Figure 1.3 Benefits of Machine Learning Algorithms.

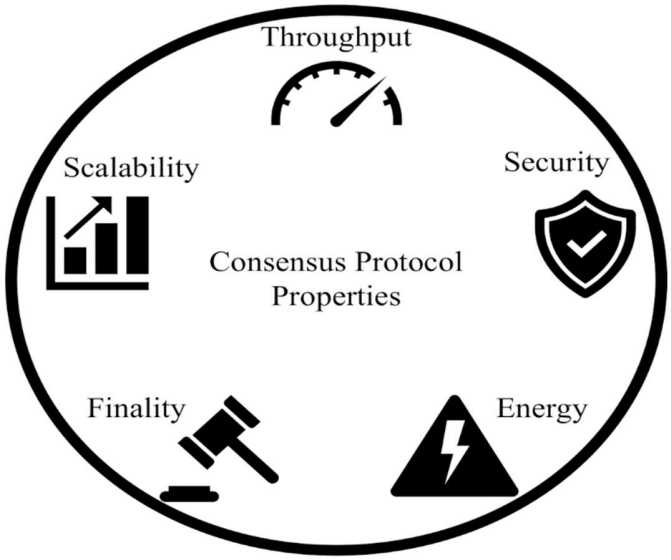


Figure 1.3: Benefits of Machine Learning Algorithms.

1.2.1 Types of Machine Learning Algorithms

Machine Learning Algorithm can be broadly classified into three types:

1. **Supervised Learning Algorithms**
2. **Unsupervised Learning Algorithms**
3. **Reinforcement Learning algorithm**

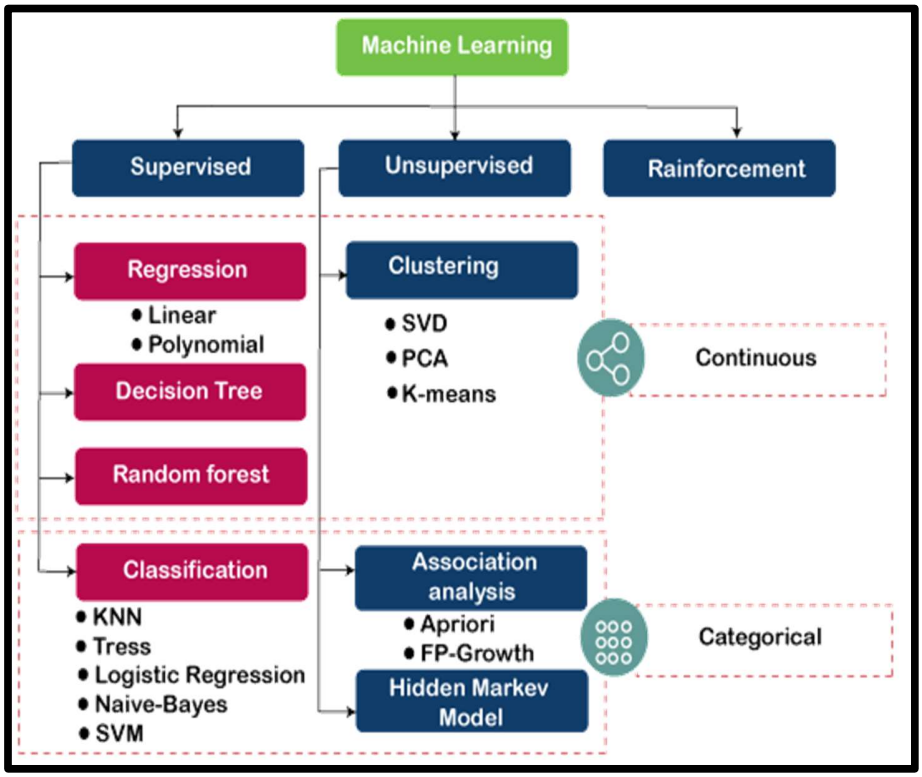


Figure 1.4: Types of Machine Learning Algorithms

1.2.2 Supervised Learning Algorithms

Input information is called preparing information and includes a known name or result such as spam/not-spam or a stock cost at a time. A show is ready through a preparing handle in which it is required to form expectations and is rectified when those forecasts are off-base. The preparing handle proceeds until the demonstrate accomplishes a wanted level of exactness on the preparing data. Example issues are classification and regression. Example calculations incorporate: Calculated Relapse and the Back Proliferation Neural

Arrange. Directed learning could be a sort of Machine learning in which the machine needs outside supervision to memorize. The administered learning models are prepared utilizing the labelled dataset. Once the preparing and handling are done, the demonstrate is tried by providing a test test information to check whether it predicts the proper output. The objective of directed learning is to outline input information with the yield information. Administered learning is based on supervision, and it is the same as when an understudy learns things within the teacher's supervision. The illustration of administered learning is spam sifting. Figure 1.5 Supervised Learning.

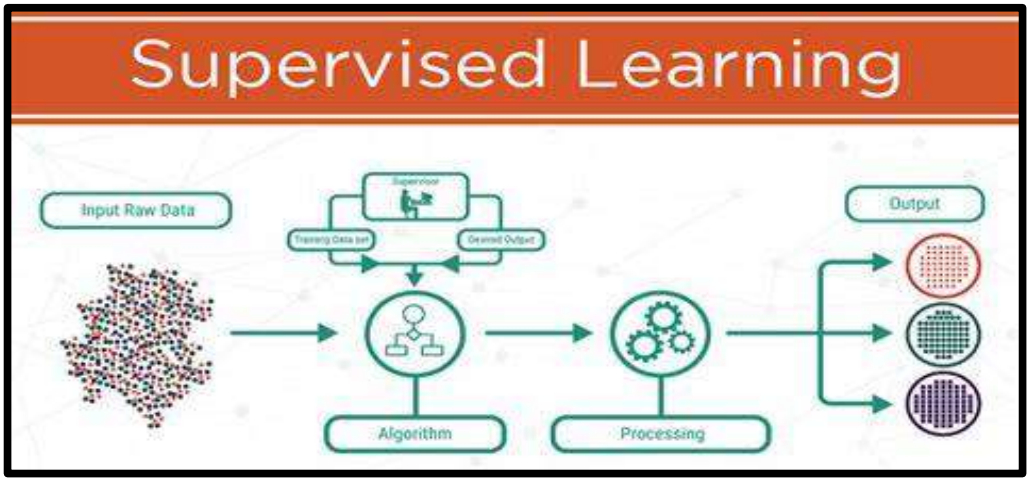


Figure 1.4: Supervised Learning

1.2.2.1 Difference between Classification and Regression

Difference between Classification and Regression is shown in the Table 1.1.

Table 1.1: Difference between Classification and Regression

S. No.	CLASSIFICATION	REGRESSION
1.	The mapping function is used for mapping values to predefined classes.	Mapping Function is used for the mapping of values to continuous output.
2.	Involves prediction of Discrete values	Involves prediction of Continuous values.
3.	Unordered Nature of the predicted data	Ordered Nature of the predicted data.
4.	Method of calculation is measuring Accuracy.	Method of calculation measurement of root mean square error.
5.	Examples are Decision tree, logistic regression, etc..	Examples are Regression tree (Random forest), Linear regression, etc.

Figure 1.5 shows the difference between Regression and Classification.

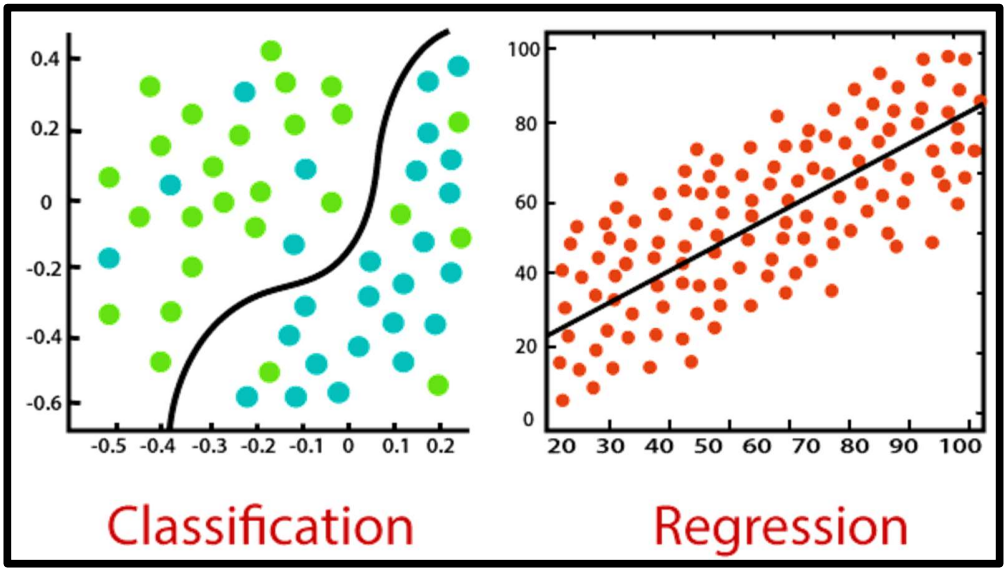


Figure 1.5: Classification vs Regression

1.2.3 Unsupervised Learning Algorithm

It could be a sort of machine learning in which the machine does not require any outside supervision to memorize from the information, consequently called unsupervised learning. The unsupervised models can be prepared utilizing the unlabelled dataset that's not classified, nor categorized, and the calculation must act on that information without any supervision. In unsupervised learning, the demonstrate doesn't have a predefined yield, and it tries to discover valuable experiences from the gigantic sum of information. These are utilized to illuminate the Affiliation and Clustering issues.

Input information isn't labelled and does not have a known result. A show is ready by finding structures display within the input information. This may be to extricate common rules. It may be through a numerical prepare to efficiently diminish excess, or it may be to organize information by similarity. Example issues are clustering, dimensionality lessening and affiliation run the show learning. Example calculations incorporate: the Apriori calculation and K-Means. Figure 1.6 shows the working of the pBFT.

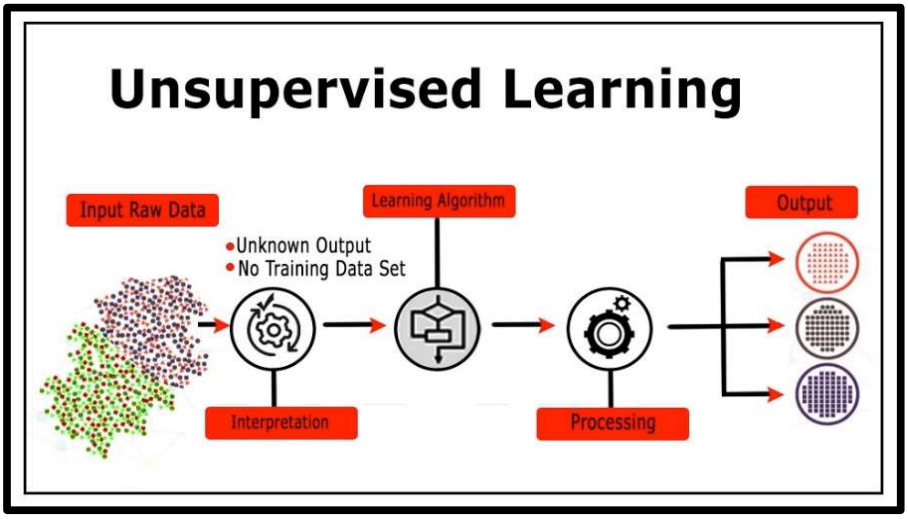


Figure 1.6: Unsupervised Learning Algorithm

1.2.4 Reinforcement Learning

- Support Learning may be a feedback-based Machine learning technique in which an specialist learns to act in an environment by performing the activities and seeing the comes about of activities. For each great activity, the operator gets positive input, and for each awful activity, the specialist gets negative criticism or punishment.
- In Support Learning, the specialist learns naturally utilizing feedbacks without any labeled information, not at all like directed learning.
- Since there's no labelled information, so the agent is bound to memorize by its encounter as it were.
- RL tackles a particular sort of issue where choice making is successive, and the objective is long-term, such as game-playing, mechanical autonomy, etc.
- The operator interatomic with the environment and investigates it by itself. The essential objective of an operator in support learning is to progress the execution by getting the most extreme positive rewards.
- It could be a centre portion of Counterfeit insights, and all AI specialist works on the concept of reinforcement learning. Here we don't have to be pre-program the operator, because it learns from its claim encounter without any human mediation.

- Case: Assume there's an AI specialist show inside a labyrinth environment, and his objective is to discover the precious stone. The operator interatomic with the environment by performing a few activities, and based on those activities, the state of the specialist gets changed, and it moreover gets a remunerate or punishment as input.
- The specialist proceeds doing these three things (take activity, alter state/remain within the same state, and get input), and by doing these activities, he learns and investigates the environment.
- The specialist learns that what activities lead to positive input or rewards and what activities lead to negative input punishment. As a positive remunerate, the operator gets a positive point, and as a punishment, it gets a negative point.

Figure 1.7 Reinforcement Learning

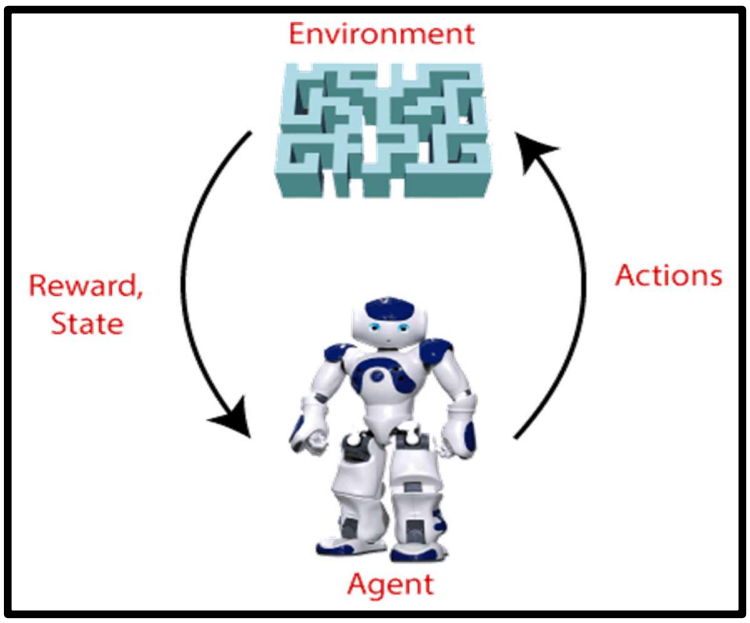


Figure 1.7: Reinforcement Learning

1.3 What is Training Data

Preparing information is additionally known as preparing dataset, learning set, and preparing set. It's a basic component of each machine learning show and makes a difference them make exact expectations or perform a wanted task. Simply put, preparing

information builds the machine learning demonstrate. It educates what the expected output looks just. Like the demonstrate analyses the dataset over and over to profoundly get it its characteristics and alter itself for way better execution.

Figure 1.8 What is Training Data

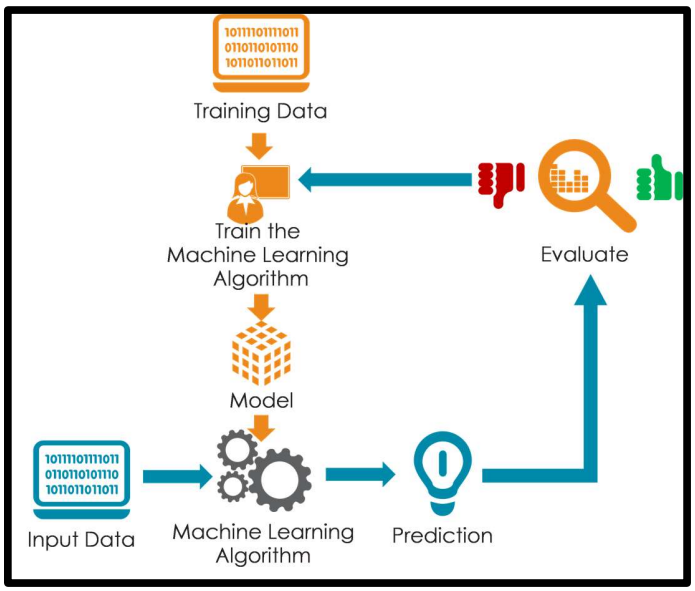


Figure 1.8: What is Training Data

Figure 1.9 Importance of data in Machine Learning.

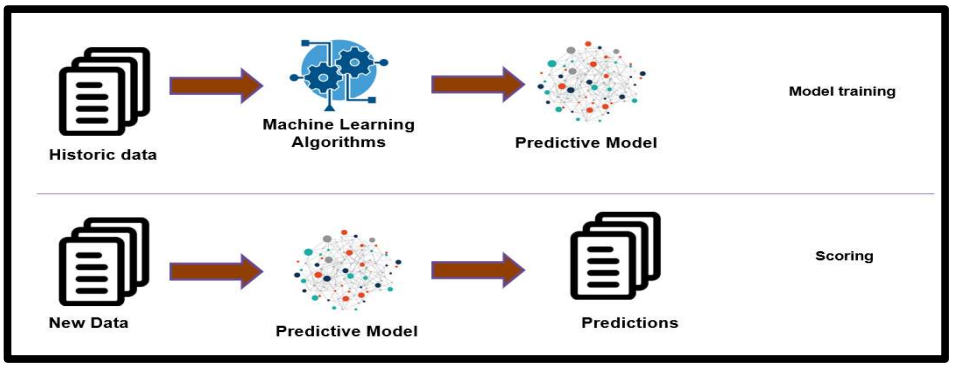


Figure 1.9 Importance of data in Machine Learning.

1.4 What Are the Components of a Machine Learning Architecture?

Outside of the specific hardware and software that compose machine learning systems, several interrelated logical components serve critical functions for machine learning systems

1.4.1 Data Generation and collection

At this arrange, information is pulled into the framework from collection destinations or databases. At this crossroads, a framework may see a generally inactive information store like a database or a steady stream of data accumulated from client interactions—for illustration, shopping behaviour from online entrances.

1.4.2 Data Pipeline

Information doesn't come in an organized format—it's up to the framework itself to clean, categorize, and structure that data, so it is usable by the machine learning calculations. The pipeline handles this by taking unstructured information, expelling fragmented or degenerate information, applying classification, and putting away that data for quick recovery.

1.4.3 Training

ML frameworks must be prepared, and as such, data is spilled into a preparing arranging range where the framework learns how to utilize that information exterior of a generation environment.

1.4.4 Evaluation

Once the preparing frameworks use the information and (ideally) learn best hones, information researchers must assess the preparing comes about to decide that what the ML framework knows is exact, profitable, and secure.

1.4.5 Prediction

Moreover, known as analytics or handling, the prepared ML framework applies its procedures to genuine information in real-world encounters.

1.4.6 Interaction

Client interfacing for the ML framework, counting dashboards, APIs, and applications give important ways for the planning group of onlookers to connected with handling comes about.

1.5 Scope of Research

The main focus of this research is to come up with a New Classifier that can help banks and its employees to provide a bank loan approval system to make Loan approval System that is fully automated based on Machine Learning.

It will use the result on the previously store manually passed data by the bank Employee.

1.6 Research Methodology

a. Referencing Machine Leaning classification research papers, smart contracts, and speaking with a machine Learning Expert.
b. The existing cloud-based approach has significant shortcomings, including security flaws, privacy concerns, and expensive management costs.
c. The idea is to create a machine leaning Classifier which will work between two Parties, one is Bank and another one is the customer who wish to apply for loan etc.

1.7 Thesis Outline

Chapter 1 describes machine learning, its advantages, the working of machine learning. Chapter 2 is dedicated to the literature review whereas in Chapter 3 Streamlit and Pickles and its use is discussed. Chapter 4 presents the deployment of Bank Loan Fraud Detection using Streamlit and Chapter 5 describes the long-term environmental aims, i.e., how the proposed system would benefit society where Chapter 6 gives the conclusion and Chapter 7 tells about the possible future work regarding the proposed Classifier and Chapter 8 contains the references of the research papers.

CHAPTER 2

LITERATURE REVIEW

A literature review covers published material in a certain topic area, as well as information published within a specific time period.

A literature review can be as basic as a summary of the sources, but it generally follows an organizational structure and incorporates summary and synthesis. A summary is a recap of the source's main information, but a synthesis is a reorganization or reshuffling of that material. It might provide a fresh take on old material or merge new and old perspectives. It might also chart the intellectual evolution of the field, including key controversies. Depending on the circumstances, the literature review may assess the sources and advise the reader on the most topical or relevant. Some of them are discussed below.

Banking system have large number of products to earn profit, but their vital source of income is from its credit system. Banking system always need accurate modelling system for large number of issues[1].

Credit scoring systems are used to model the potential risk of loan applications, which have the advantage of being able to handle a large volume of credit applications quickly with minimal labour, thus reducing operating costs, and they

may be an effective substitute for the use of judgment among inexperienced loan officers, thus helping to control bad debt losses. This study explores the performance of credit scoring models using traditional and artificial intelligence approaches: discriminant analysis, logistic regression, neural networks and classification and regression trees[15].

This study proposes a Decision-Tree Credit Assessment Approach to solve the credit assessment problem under a big data environment[14].

Finance is the biggest factor of the Banking Industry. In Banking Industry success and failure is based on the credit. Banking Industries are competitive today with increase in volume, velocity and variety of new and existing data. Managing and analysing the massive data is more difficult.

This model uses data mining techniques such as decision tree, Support vector machine and logistic regression and it provides the information to make decision on loan proposals using wekatool[13].

Banks and financial institutions rely on loan default prediction models in credit risk management. An important yet challenging task in developing and applying default classification models is model evaluation and selection. This study proposes an evaluation approach for bank loan default classification models based on multiple criteria decision making (MCDM) methods. A large real-life Chinese bank loan dataset is used to validate the proposed approach. Specifically, a set of performance metrics is utilized to measure a selection of statistical and machine-learning default models. The technique for order preference by similarity to ideal solution (TOPSIS), a MCDM method, takes the performances of default

classification models on multiple performance metrics as inputs to generate a ranking of default risk models. In addition, feature selection and sampling techniques are applied to the data pre-processing step to handle high dimensionality and class unbalanced Ness of bank loan default data. The results show that K-Nearest Neighbour algorithm has a good potential in bank loan default prediction[12].

This paper describes a study on the empirical comparison of classification techniques for predictive ranking of the 12-month risk of default in banks. This work compares the scoring capabilities of different predictive models. This comparison demonstrates that inductive machine learning techniques can be successfully applied for predictive ranking of default risk. Observed results indicate better performance by symbolic rule or decision tree based models than by traditional modeling techniques based on statistical algorithms[11].

in this paper we endeavour to lessen this hazard factor behind choosing the protected individual to spare heaps of bank endeavours and resources. The primary target of this paper is to anticipate in the case of allotting the loan to specific individual will be protected or not. This paper is separated into four segments Data Collection Comparison of machine learning models on gathered data Training of framework on most encouraging model Testing[10].

The domain is data mining so we are using data mining techniques to analyze risk giving loan. It includes analysing and processing data from various resources and summarise into a valuable information. We are using C4.5 classification algorithm

of Data mining. Early data analysis techniques were oriented toward extracting quantitative and statistical data characteristics[9].

These techniques facilitate useful data interpretations and can help to get better insights into the processes behind the data. Although the traditional data analysis techniques can indirectly lead us to knowledge, it is still created by human analyst. The banks and many investment companies are pioneers in taking advantage of Data Mining.

To predict, the system needs information of a person which will be read by the system via dynamic web page which are analysed. Decision tree learning algorithms are been successfully used in expert systems in capturing knowledge. The main work performed in this system is using inductive methods to the attributes of an unknown object to determine appropriate classification according to decision tree rules. These parameters are used to compare the three different kind of decision tree algorithms[7].

As the reform and opening up going into depth over the past three decades and more, the market economic system has been gradually established. It supports economic development, reduces and defends many financial risks in the process of the reform. Therefore, people should focus on how to accurately classify the banking loans into performing and non-performing ones and how to control and prevent the resulting crisis.

This paper deeply analyses China's NPLs problem for the current period, recognizes and classifies loans types by adopting decision trees, Naïve Bayes and support vector machine methods[6].

This study was conducted to study the classification of decision with C4.5 Algorithm which is implemented in analysing the survival of the UKM that recorded in public Official UKM. The result of data mining test using decision tree classification with C4.5 Algorithm able to describe from root node to tree structure that determine the survive or not survive of the UKM[5].

So, in this paper we try to reduce this risk factor behind selecting the safe person so as to save lots of bank efforts and assets. The main objective of this paper is to predict whether assigning the loan to particular person will be safe or not. This paper is divided into four sections Data Collection Comparison of machine learning models on collected data Training of system on most promising model Testing[3],Data mining techniques are becoming very popular nowadays because of the wide availability of huge quantity of data and the need for transforming such data into knowledge. Banking systems collect huge amounts of data on day-to-day basis, be it customer information, transaction details like deposits and withdrawals, loans, risk profiles, credit card details, credit limit and collateral details related information. In recent years the ability to generate, capture and store data has increased enormously. The information contained in this data can be very important.

The wide availability of huge amounts of data and the need for transforming such data into knowledge encourage IT industry to use data mining. Data mining techniques are greatly used in the banking industry which helps them compete in the market and provide the right product to the right customer with less risk. Data mining techniques like classification and prediction can be applied to overcome

this to a great extent. Induction Data Mining Algorithm is applied to predict the attributes relevant for credibility[16].

- X. Liang, S. Shetty, Kandala Meenakshi, et al. [9], discussed in their paper that cloud data provenance is metadata that tracks the history of a cloud data object's creation and actions. Data accountability, forensics, and privacy all rely on secure data provenance. In this work, author propose a Machine Learing-based decentralised and trustworthy cloud data provenance architecture. Machine Learing-based data provenance can give tamper-proof records, provide data accountability transparency in the cloud, and aid to improve the privacy and availability of provenance data. To gather provenance data, author employ the cloud storage scenario and the cloud file as a data unit to identify user actions. By incorporating provenance data into Machine Learing transactions, author develop and build ProvChain, an architecture for collecting and verifying cloud data provenance. ProvChain works in three stages: (1) collecting of provenance data, (2) storage of provenance data, and (3) validation of provenance data. According to the results of the performance study, ProvChain delivers security characteristics such as tamper-proof provenance, user privacy, and dependability with little overhead for cloud storage applications.

- X. Wang, X. Xu, L. Feagan, S. Huang, L. Jiao, et al. [10], discussed in their paper that the real-time gross settlement system (RTGS) is the foundation of interbank payment transactions. The extraordinary growth of large-value wholesale payments has compelled financial institutions to create inter-bank payment systems (IBPS) with better levels of throughput, security, and stability. This intriguing method to IBPS orchestration makes use of developing Machine Learing technology, which has been successfully used to provide distributed trust and secrecy for a variety of financial industry applications. However, Machine Learing is not a panacea for IBPS, which faces several issues because of high-value transactions. Financial institutions anticipate not just a straightforward

transition from traditional RTGS to a Machine Learing platform, but also a decentralised system with improved secrecy, instruction settlement finality, a liquidity preservation mechanism, and more efficient gridlock resolution mechanisms. Author provide an end-to-end IBPS prototype built on the Hyperledger Fabric enterprise Machine Learing platform in this article. For interbank payment activity, the prototype enables gross settlement, impasse resolution, and reconciliation. As part of the early study for the Ubin Project, this prototype has been shown to deliver a better degree of payment settlement service.

- Salar Ahmadisheykhsarmast, Rifat Sonmez, et al. [11], discussed in their paper that Project participants must be paid on time for construction projects to be completed successfully; unfortunately, the construction sector globally suffers from inadequate payment procedures. Existing research investigated the causes and implications of the payment dilemma, but relatively few studies suggested solutions. This article introduces SMTSEC, a unique smart contract payment security solution designed to eliminate or reduce payment concerns in the construction industry. The SMTSEC maintains the security of construction contract payments using an automated computerised system based on a decentralised Machine Learing. An actual construction project is used to investigate the potential contributions and limits of the proposed SMTSEC. The SMTSEC's key value is that it provides a new mechanism for timely and transparent payment of construction projects by assuring security of payment for works in progress without the administrative fees and responsibilities of trusted middlemen such as attorneys or banks.

- Lin Zhong, Qianhong Wu, et al. [12], discussed in their paper that off-chain payments are a critical strategy for increasing the scalability of Machine Learing-based cryptocurrencies. However, because tokens locked in off-chain channels cannot be transferred from one channel to another, current off-chain payment systems have capacity limitations. Author’s offer a secure large-scale immediate payment (SLIP) method in this paper to boost the capacity of Machine Learing

networks. The SLIP mechanism connects some of the off-chain channels with an aggregate signature scheme, allowing tokens locked in these channels to move from one to the next. As a result, the quantity of tokens distributed in these channels is the sum of all locked-in tokens rather than the minimum locked-in tokens. In other words, it enhances the negotiability of tokens trapped in these linked off-chain channels. Furthermore, because payers may accumulate signatures gradually, payees only need to check a line of transactions once in each transaction, whereas nodes (miners) that maintain the Machine Learing system only need to validate all transactions once, making the SLIP system incredibly efficient. Authors demonstrated that the SLIP system is secure if the underlying Machine Learing system is secure and aggregate signature fulfils aggregate chosen-key security. Finally, evaluations demonstrate that the SLIP system has a far bigger capacity than the Lightning Network.

- H. Singh and A. Dubey, et al. [13], discussed in their paper that traditional electronic payment methods have challenges with ensuring safety, trust, and accuracy. Machine Learing technology has the potential to address these issues. The bibliometric trends of Machine Learing technology and electronic payments research show that China, Chinese authors, and Chinese universities dominate the subject. China was followed by the United States of America. The main journals were IEEE Access and Lecture Notes in Computer Science. Future research might concentrate on expanding the use of Machine Learing technology in electronic payments, and future researchers could concentrate on papers and resources from China and the United States of America for knowledge updates and research collaborations**.**

- S. Joseph and S. Karunan, et al. [14], discussed in their paper that Machine Learing, the underlying technology underpinning Bitcoin, is a new industry technology. Machine Learing has the potential to improve existing corporate processes by making them more democratic, transparent, secure, and efficient.

Banking industry are the first to capitalise on this technology's disruptive potential. The Indian banking system is one of the most complicated bank payment systems on the planet. The present infrastructure utilised by Indian banks is a real-time gross settlement system with a centralised design. Transaction processing is sluggish and cumbersome as a result of this centralised design. It also results in a significant quantity for security and recovery considerations. The real-time gross settlement system necessitates a high level of security, robustness, and performance. The primary goal is not to migrate from old systems to Machine Learing platforms, but to create a system that provides security, secrecy, and a decentralised money lending mechanism. A unique method is suggested here that enables a decentralised banking system and services based on the Ethereum Machine Learing platform. Using distributed ledger technology, the system supports several services such as money deposit, money transfer, and loan checking, among others.

- N. P. Pravin, K. P., et al. [15], discussed in their paper that people's lives have been transformed as digital technology has advanced. Many dangers and scams have been found in the financial sector. Banking systems employ centralised databases, which allows attackers easy access to data and renders the system unsafe. The disadvantage of this centralised system may be mitigated by restructuring the system through the use of Machine Learing technology without the need of tokens. For storing and accessing data in a database, Machine Learing employs a decentralised design. This lower compromised database attacks. Transactions made using Machine Learing technology are validated by each block in the chain, making the transaction more secure and allowing the financial system to operate more quickly.

- Lin Zhong, Qianhong Wu, Jan Xie, et al. [16], discussed in their paper that in the present Machine Learing systems, ever-increasing transaction fees, severe network congestion, and poor transaction rates limit their widespread adoption.

Author proposes a secure versatile light payment (SVLP) system to alleviate this problem. The SVLP uses only a digital signature algorithm and a one-way function, and its security is comparable to that of existing Machine Learing systems such as Bitcoin and Ethereum. The suggested approach consumes very little power since payers and payees only need one-way functions to complete repeated transactions, rather than the costly digital signature algorithms. Furthermore, the payment and refunding methods are adaptable. This is because the denomination in our scheme is divisible, and users do not need to check the preimages on the lengthy chain one by one. Finally, because the transaction may be performed off-chain and offline, it can be utilised in rural places or areas affected by natural disasters when communication infrastructure is lacking or damaged. All of these characteristics show that our strategy is both practical and adaptable.

- Mohanty, Debasis, et al. [17], discussed in their paper that interoperability protocols are required for Machine Learing-technology uptake due to the widely fragmented Machine Learing and cryptocurrency environment. The immediate consequence of interchain interoperability is automated cryptocurrency switching. A comprehensive study of the available literature on Machine Learing interoperability and atomic cross-chain transactions was conducted. Author researched many Machine Learing interoperability options, including industrial solutions, classified them, defined the major mechanisms employed, and provided numerous examples for each category. Author concentrated on atomic transactions across Machine Learings, often known as atomic swap. Furthermore, author investigated contemporary atomic swap implementations as well as architectural approaches, and author derived research difficulties and obstacles in cross-chain interoperability and atomic swap. Atomic swap may quickly transfer tokens while drastically lowering related costs without the use of centralised authority, facilitating the construction of a sustainable payment system for greater financial inclusion.

- C. V. N. U. B. Murthy, M. L. Shri, et al. [18], discussed in their paper that Machine Learing technology is a distributed ledger with data records covering all information of transactions carried out and disseminated across network nodes. All transactions in the system are validated by consensus procedures, and once recorded, data cannot be changed. Machine Learing technology is the enabling technology for Bitcoin, a prominent digital cryptocurrency. "Cloud computing is the technique of storing, managing, and processing data on a network of remote computers housed on the internet rather than a local server or a personal computer." It still faces several issues such as data security, data management, compliance, and dependability. In this post, author discussed some of the major difficulties that the cloud faces and provided solutions by combining it with Machine Learing technology. Author will conduct a quick review of previous studies focusing on Machine Learing integrating with the cloud to demonstrate their superiority. In this study, authors also created an architecture that integrates Machine Learing and cloud, demonstrating the connection between Machine Learing and cloud.

- J. Sidhu, et al. [19], discussed in their paper that while Bitcoin [Nik] solved the double spend problem and offered work with timestamps on a public ledger, it has not yet expanded the capabilities of a Machine Learing beyond a transparent and public payment system. Satoshi Nakamoto's first reference client had a decentralised marketplace service that was eventually discontinued owing to a lack of resources [Deva]. Author built on Nakamoto's vision by developing a set of commercial-grade services that support a wide range of business use cases, such as a fully developed Machine Learing-based decentralised marketplace, secure data storage and transfer, and unique user aliases that connect the owner to all services controlled by that alias.

- F. Gao, L. Zhu, et al. [20], discussed in their paper that a component of V2G networks, EVs receive power not only from the grid but also from other EVs and may regularly send the power back to the grid. Payment records in V2G networks may be used to extract user habits and make better decisions about power supply, scheduling, pricing, and consumption. However, sharing payment and user information presents major privacy concerns, on top of the current problem of safe and dependable transaction processing. In this paper, author propose a Machine Learing-based payment method for V2G networks that allows data exchange while protecting sensitive user information. The method presents a registration and data maintenance procedure based on a Machine Learing approach, which maintains user payment data confidentiality while allowing payment audits by privileged users. Our concept is deployed using Hyperledger to ensure its practicality and efficacy.

- Qinghua Lu, Xiwei Xu, et al. [21], discussed in their paper that Machine Learing-based payments have piqued the interest of everyone from amateurs to corporations to regulatory authorities as the game-changing use of Machine Learing technology. Machine Learing enables quick, safe, and cross-border payments without the use of intermediaries like banks. Because Machine Learing technology is still in its early stages, systematic knowledge that provides a holistic and comprehensive view on creating Machine Learing-based payment applications has yet to be produced. If such information could be produced in the form of a collection of Machine Learing-specific patterns, architects may utilise those patterns to develop a Machine Learing-enabled payment application. As a result, in this paper, author first define a token's lifetime before presenting 12 patterns that address essential elements of allowing token state transitions in Machine Learing-based payment systems. The lifecycle and annotated patterns give a payment-focused systematic perspective of system interactions as well as guidance on how to apply the patterns effectively.

- N. El Madhoun, F. Guenane, et al. [22], discussed in their paper that NFC technology is now employed in contactless payment applications, with NFC payment capabilities available in credit/debit cards, smartphones, and payment terminals. As a result, an NFC payment transaction is carried out in a straightforward and practical manner. EMV is a security protocol that applies to both contact and contactless payment systems. However, during an EMV payment transaction, this standard does not enforce the following two major security limitations between a client payment device and a payment terminal: (1) mutual authentication and (2) confidentiality of sensitive financial data transferred. Because the transaction is done via NFC radio waves in an open environment, these flaws pose a significant danger in the case of NFC payment. Contact payment reduces risk since the transaction is completed in a closed environment by putting the card into the terminal. Author presents a novel security protocol for NFC payment transactions based on a Cloud architecture in this study. Author use the Scyther tool, which gives formal proofs for security protocols, to validate this proposal.

- Z. Wang, et al. [23], discussed in their paper that computing is causing a big change in e-business. Software, platforms, and infrastructure arrive on the Internet one after the other, extending the electronic business chain and becoming the most recent paradigm known as entire e-business. This thesis proposes a cloud computing-based online payment method after examining cloud computing theories and the constraints of existing online payment models. The mode's organisational structure, technical architecture, and business processes have been designed and analysed to serve as references for establishing collaboration with the "four chains" - commerce chain, capital chain, logistics chain, and government chain - and realising the integration of banking system and entity industry system.

- S. Wang, Y. Wang, et al. [24] discussed in their paper that today, an increasing number of businesses and people are outsourcing their data to cloud storage

systems. Data deduplication is an important technology for lowering the storage costs of cloud storage systems. The customer can outsource the data files to the cloud storage server and pay for them in a cloud storage system using deduplication technology. One of the most important difficulties in the cloud deduplication storage system is fair remuneration. Currently, a number of safe deduplication encryption algorithms have been developed to ensure client data privacy. However, most contemporary fair payment solutions produce payment tokens using standard electronic currency systems, which necessitates the employment of a trusted authority to avoid double-spending. Trusted authority will become payment system bottlenecks. To address this issue, author propose a new decentralised fair payment mechanism for cloud deduplication storage systems using Ethereum Machine Learing technology in this study. The new protocol takes use of Machine Learing technology's decentralisation by allowing direct transactions without the need of trusted third parties. If a malevolent circumstance happens in the new protocol, the system may ensure fair payment by pre-storing penalty money in the smart contract. Author novel procedure is practical, according to both safety and experimental evaluations.

- X. Lei, T. Xie, et al. [25] discussed in their paper that bitcoin (BTC) payments have grown in popularity among retailers and service providers in recent years. A BTC transaction (tx) requires six confirmations (one hour) to be validated, excluding it from fast-pay situations. In theory, a shorter waiting time period enhances the likelihood of a successful double-spending assault. To overcome this issue, author propose the BTCFast scheme, which supports quick BTC transfers. BTCFast is a unique, decentralised, escrow-based system built on top of Machine Learings with programmable smart contracts (PSC) (e.g. Ethereum, EOS). Author create a smart contract (PayJudger) to operate as a trustworthy payment judger, ensuring the tx fairness. Furthermore, author design a payment judging method based on proof-of-work (PoW) for PayJudger to decide a BTC payment dispute. Our theoretical and practical results suggest that BTCFast may cut the waiting time

to less than 1 second while maintaining equivalent security to the present strategy (i.e., waiting for six confirmations) and incurring no additional operating fees.

- Y. Li, et al. [26] discussed in their paper that while smart contracts have enabled a wide range of applications in many public Machine Learings, such as Ethereum, their security flaws have raised a growing number of risks to the ecosystem's stability. In actuality, many external assaults against smart contracts are the consequence of failed payments using digital assets such as bitcoins. While a growing number of research papers have been published on such issues, many of them have used pattern-based heuristics (e.g., reentrancy) to detect payment-related assaults, which can result in a significant number of false positives and negatives. In order to overcome these constraints and improve payment security on Machine Learing, we established a new class of payment attacks in this work, namely, unfair payment attacks (UP). UP conceptually encompasses a broader spectrum of payment assaults than previous heuristics. Furthermore, author emphasised the SAFEPAY generic architecture for comprehensively detecting UP. The essential finding is a new security invariant called fair value exchange (FVE), which simulates the fairness of Machine Learing payments between several participants. SAFEPAY, in particular, explores the transaction space of a given smart contract methodically and generates a restricted set of transaction sequences. SAFEPAY reports a UP assault for each sequence after an FVE violation is established. SAFEPAY for Ethereum has been further instantiated and used in real-world smart contracts. In the empirical examination, SAFEPAY was able to detect previously unknown UP assaults while efficiently avoiding false alarms when compared to other analysers in the literature.

- X. Zhao and Y. -W. Si, et al. [27] discussed in their paper that academic certificates are still commonly awarded on paper nowadays. Traditional certificate verification is a time-consuming, labor-intensive, and even costly procedure. In this research, author offer NFTCert, a novel NFT-based certificate system that allows for the

construction of linkages between a legal certificate and its owner through a Machine Learing. Author explain the NFTCert framework's implementation in this paper, covering schema definition, minting, verification, and revocation of NFT-based certificates. In addition, we incorporate a payment mechanism into the minting process, allowing NFTCert to be utilised by a broader audience. As a result, NFTCerts participants do not need to rely on cryptocurrencies for transactions. When compared to existing Machine Learing-based systems, the proposed framework is meant to provide usability, authenticity, secrecy, transparency, and availability features.

- Y. Chen, X. Li, et al. [28] discussed in their paper that the transaction throughput and latency of Machine Learing-based coins are severely constrained. A payment channel, which facilitates trust-free payments between two peers without draining the Machine Learing's resources, is a possible solution to this problem. A connected payment channel network (PCN) allows payments to be made between two peers via a number of intermediary nodes that forward and charge for the payments. However, most existing ideas merely employ the shortest path as the transaction path, causing frequently repeated channels to be soon depleted. Furthermore, the majority of existing PCNs are virtually exclusively designed for payments between two parties, resulting in limited application scenarios. The two-party PCNs cannot perform simultaneous payments when several payments use the same intermediate channel. In this study, author offer a multi-party payment channel (MPC) network, a payment channel proposal that permits several payments over the same intermediate channel at the same time, considerably increasing payment channel application possibilities. Furthermore, our channel selection and transaction conversion tactics can improve transaction success rates. Author build the MPC network in the Truffle-based simulated Machine Learing network and lightning network, and a significant number of trials validate the usefulness of our approach.

- C. Wu, J. Xiong, et al. [29] discussed in their paper that in its most basic form, a smart contract is a piece of computer programme code comprising associated economic transactions and algorithms. This is essentially the computerization of the previously agreed-upon contract between the participants. When certain circumstances are met, this customised contract agreement is immediately evaluated and implemented. Smart contracts are utilised not just in financial transactions, but also in many sectors of social life. Although smart contract technology offers distinct advantages, it is still in its early phases of development, with numerous issues yet to be resolved. This article first quickly covers the Machine Learing development process before focusing on the research progress of Machine Learing 2.0-smart contracts. Second, the associated ideas of smart contracts are explained, as well as the functioning mechanism of smart contracts and the challenges that smart contracts confront. Finally, in response to these issues and quandaries, the relevant remedies and concepts are described, and the future difficulties and development patterns of smart contracts are studied and evaluated.

- Mahmoud Saleh Obaid, et al. [30] discussed in their paper that Mobile payments are becoming the preferred way of payment for a growing number of clients. Providing an effective security mechanism for mobile payments in public networks is a difficult challenge for device manufacturers and network service providers. Although most mobile payment applications make payments simple and quick, customers must contend with new security risks. Because users must conduct money transactions over an open network, their sensitive data is put at danger, allowing advisories to launch attacks and steal user identifying information. Recent payment applications, such as Google-pay and phone-pay, have effectively addressed security concerns; nonetheless, these apps may be vulnerable to internal assaults since data is centralised, and apps must obtain authorization from bank servers to conduct transactions. Author establish a protected transaction pattern utilising Machine Learing technology in the proposed

system, which addresses the limitations of the present system. Our money is converted into bitcoins and stored in a separate wallet. The wallet is installed on the mobile devices. Payment or transaction between two consumers without previous approval. To protect data privacy from attackers, the suggested System employs a decentralised data server. During the transaction, author transmit funds directly through the Machine Learing wallet, bypassing the bank. For online payment transactions, the suggested solution proved to be secure and efficient. Because it is protected against cyber attackers or hackers, data can be kept in different blocks, making it difficult to identify specific data. This eliminates the disadvantage of traditional mobile payments.

- X. Pei, L. Sun, et al. [31] discussed in their paper that while multiple party computation (MPC) has been proposed for over two decades, author have yet to see implementations that make MPC or its derivatives a tangible reality. Difficulties originate from recurring security and trust difficulties, which often manifest as data leakage, sloppy computation, and payment denial, among other things. Many solutions rely on a third party to coordinate parties co-working; however, each participant must completely trust the third party and entrust the source data and payment to it. In this research, author propose a Machine Learing-based protocol for efficient MPC without the need for a trusted third party. A zero-knowledge coordinator handles collaboration and work scheduling, while smart contracts manage user requests and secure payment. Cryptography techniques are used to maintain secrecy, privacy, and verifiability. All data is transported and computed in the encryption state, and only the user who has paid may decode the computation result.

- Zhaoxuan Li, Rui Zhang, et al. [32] discussed in their paper that the smart contract is gaining popularity as a basic component of the Machine Learing. However, the regular occurrence of smart contract security incidents demonstrates that smart contract security must be improved. It is yet unclear how to ensure both the secrecy

of contract execution and the accuracy of computation outputs at the same time. One potential option is to use secure multi-party computation (SMPC) technology to construct smart contracts. However, a concern has been overlooked in previous SMPC-based contract execution schemes: the attacker can conduct the same procedure as the reconstructor to recover the secret, resulting in the disclosure of users' privacy. As a result, in order to address this issue throughout the smart contract operation process, this research proposes an improved homomorphic encryption method with a minimal public key size, low ciphertext length, and good encryption efficiency. Then, a contract execution system combined with SMPC and homomorphic encryption (SMPC-HE for short) is developed, which can guarantee contract execution privacy while also ensuring the correctness of calculation results, and also makes smart contract execution fairer. Finally, theory and empirical findings show that our approach is safe, efficient, and has a minimal space overhead.

- X. Luo, W. Cai, et al. [33] discussed in their paper that because crypto currency users are compelled to relinquish their private keys to the exchange, traditional centralised token exchanges (CEX) are criticised for their security and privacy vulnerabilities. In contrast, a decentralised token exchange (DEX) overcomes this problem by adding a trading gas cost and delay to the system. To combine the benefits of CEX and DEX, a hybrid decentralised token exchange (HEX) has been suggested. However, current HEX is still plagued by two flaws. The first issue is that it is inconvenient for a trader who has to swap tokens frequently within a specific time frame because it is time-consuming and costly. The second problem is the possibility of Ethereum network congestion caused by the exchange's excessive simultaneous transactions. Author suggests a payment channel-based HEX in this research, which extends current systems by introducing a new payment channel layer to assist frequent traders and relieve network congestion.

- P. Frauenthaler, M. Sigwart, et al. [34] discussed in their paper that current Machine Learing relay systems need the destination Machine Learing to validate each relayed block header immediately. When establishing these relays across Ethereum-based Machine Learings, where verifying block headers on-chain is computationally difficult, this results in significant running costs. To address these restrictions, author provide an unique relay system that combines a validation-on-demand pattern with economic incentives to lower the cost of running a relay across Ethereum-based Machine Learings by up to 92 percent. Decentralized interoperability between Machine Learings such as Ethereum and Ethereum Classic becomes possible with this relay method.

- D. Kaid and M. M. Eljazzar, et al. [35] discussed in their paper that motivated by the current disruption in changing sectors through Machine Learing, this research investigates the impact of combining Machine Learing and Enterprise Resource Planning systems on the relationships between supply chain participants. Distributors aim to automate payments with retailers under certain conditions in order to establish a smooth integration, which may be accomplished using smart contracts on a Machine Learing network. In this research, author investigate the use of QR codes to manage such scenarios in the supply chain business, namely between distributors and retailers. Then, author look at how Machine Learing may help in these situations. Furthermore, a prototype is constructed and developed using Hyperledger Composer to highlight the benefits of Machine Learing in a supply chain. This prototype emphasises the increased value Machine Learing may have on the relationship between the two supply chain participants, while also giving additional capabilities to help both sides create the necessary trust.

CHAPTER 3

STREAMLIT AND PICKLE

INTRODUCTION

Pickle may be a bland protest serialization module that can be utilized for serializing and deserializing objects. Whereas it's most commonly related with sparing and reloading prepared machine learning models, it can really be utilized on any kind of question.

Pickle could be a module in Python utilized for serializing and de-serializing Python objects. This changes over Python objects like records, lexicons, etc. into byte streams (zeroes and ones). You'll change over the byte streams back into Python objects through a handle called unpickling. Pickling is additionally known as serialization, straightening, or marshaling.

Streamlit is an open source app system in Python dialect. It makes a difference us make web apps for information science and machine learning in a brief time. It is congruous with major Python libraries such as scikit-learn, Keras, PyTorch, SymPy(latex), NumPy, pandas, Matplotlib etc. With Streamlit, no callbacks are required since widgets are treated as factors. Information caching disentangles and speeds up computation pipelines. Streamlit observes for changes on overhauls of the connected Git store and the application will be sent naturally within the shared connect.

3.1 How to Pickle

The pickle module has two methods.

pickle.dump()

The `pickle.dump()` method dumps the Python object in the pickle file. This creates a `.pickle` file in your current working directory (`pickle.dump(what_are_we_dumping, where_are_we_dumping_it)`):

```
import
pickle

        example_dict = {1:"Australia", 2:"Belgium", 3:"Canada", 4:"Denmark"}

        #statement 1
        with open('example_dict.pickle', 'wb') as pickle_out:
          pickle.dump(example_dict, pickle_out)

        #statement 2
        pickle_out = open("example_dict.pickle", "wb")
        pickle.dump(example_dict, pickle_out)
        pickle_out.close()
```

In the code snippet above, we are creating an example_dict.pickle file from an example_dict dictionary. Statements 1 and 2 perform the same task of converting the dictionary into a pickle file. Using the with statement ensures that open file descriptors are closed automatically after the program execution leaves the context of the with statement. The 'wb' in the open statement means we are writing bytes to file.

pickle.load()

The pickle.load() method lets you use the .pickle file (pickle.load(what_do_we_want_to_load)) by loading it in the memory:

```
#statement
1
            pickle_in = open("example_dict.pickle", "rb")
            example_dict = pickle.load(pickle_in)

            # statement 2
            example_dict = pickle.load(open("example_dict.pickle", "rb"))
```

In the code snippet above, we are creating an example_dict dictionary from an example_dict.pickle file. Statements 1 and 2 perform the same task of reading the pickle file, which is a dictionary. The 'rb' in the open statement means that we are reading byte data from the file.

When Not to Pickle

- When working with multiple Python versions: Unpickling objects pickled in different Python versions can be a hassle.
- When working across multiple languages: The data format used by pickle is Python-specific, which means that non-Python programs may not be able to reconstruct pickled Python objects.
- When working with a recursive data structure: Trying to pickle a highly recursive data structure may exceed the maximum recursion depth. A RuntimeError will be raised in this case. You can raise this limit with sys.setrecursionlimit().

- When working with an external pickle file: The pickle module is not secure. Only unpickle the data that you trust. It is possible to construct malicious pickle data that will execute arbitrary code during unpickling. Never unpickle data that could have come from an untrusted source.

3.2 How to Streamlit

The slant of Information Science and Analytics is expanding day by day. From the information science pipeline, one of the foremost imperative steps is demonstrate arrangement. We have a parcel of alternatives in python for conveying our demonstrate. A few well-known systems are Carafe and Django. But the issue with utilizing these systems is that we ought to have a few information of HTML, CSS, and JavaScript. Keeping these prerequisites in intellect, Adrien Treuille, Thiago Teixeira, and Amanda Kelly made "Streamlit". Now utilizing streamlit you'll
send any machine learning demonstrate and any python extend with ease and without stressing approximately the frontend. Streamlit is exceptionally user-friendly.
An intuitively and Instructive dashboard is exceptionally fundamental for way better understanding our information sets. This will offer assistance an analyst for getting distant better; a much better; a higher; a stronger; an improved">a much better understanding of our comes about and after that, an analyst can make a few fundamental changes for way better understanding. Visual Reports is must superior than in Number format for fast understanding. In straightforward words, Streamlit could be a exceptionally straightforward and simple way to make a dashboard that makes a difference us to form an productive, compelling, and informative dashboard. Streamlit is an open-source web application system which makes the work basic for data analyst by examining and understanding data by implies of a dazzling dashboard. No front-end knowledge is required for working with Streamlit. This system will convert data scripts into a shareable web application in few lines of codes and fair in a couple of seconds as well. In this article, we are getting to examine how to make an intelligently dashboard in Python utilizing Streamlit.

```
pip install streamlit
```

3.3 Working of Streamlit

Working with Streamlit is simple. First you sprinkle a few Streamlit commands into a normal Python script, and then you run it. We list few ways to run your script, depending on your use case.

Use streamlit run

Once you've created your script, say your_script.py, the easiest way to run it is with streamlit run:

streamlit run your_script.py

As soon as you run the script as shown above, a local Streamlit server will spin up and your app will open in a new tab your default web browser

Pass arguments to your script

When passing your script some custom arguments, they must be passed after two dashes. Otherwise the arguments get interpreted as arguments to Streamlit itself:

streamlit run your_script.py [-- script args]

Pass a URL to streamlit run

You can also pass a URL to streamlit run! This is great when your script is hosted remotely, such as a Github Gist. For example:

streamlit run https://raw.githubusercontent.com/streamlit/demo-uber-nyc-pickups/master/streamlit_app.py

Run Streamlit as a Python module

 # Running

python -m streamlit your_script.py

 # is equivalent to:

streamlit run your_script.py

One such example of Streamlit working is shown in the below figure 3.2.

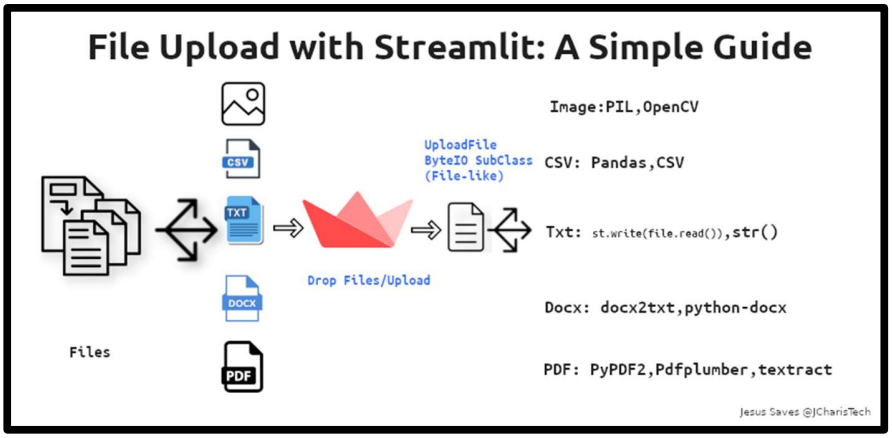


Figure 3.2 Working of Streamlit

3.4 Benefits of smart contract

a) Easy to learn- almost no learning curve
b) User-friendly (Developer-Friendly)
c) Less time-taking to build
d) 3rd-party integrations for graphs

CHAPTER 4

DEPLOYMENT OF BANK LOAN FRAUD DETECTION USING ML

Overview

Our proposed framework may be a Bank Credit Extortion Location Utilizing ML. Earlier to the revelation of the Machine Learning, mannual framework played a major part in empowering the Fast communication between two parties. But it had certain issues and that's when streamlit and Machine Learning came into picture.

Streamlit is an essential program that run when need to output a User Interface (UI) in the system. They are often used to automate the implementation of an GUI very easily so that all participants may be confident of the conclusion instantly, without the GUI user may need to face difficulties or time lost.

Other Machine Learning based systems used other Technologies like Pyhton Flask etc. that leads to little more complex programming so in Our suggested System we use the Streamlit to develop the UI and implement the Machine Learning Based classifier Model.

We employed Bank Loan Fraud Detection using ML in the proposed solution to eliminate any third parties. We utilised ethers to deploy the Classifier on the streamlit Heroku Platform. Machine Learning Classifier are a collection of computer programmes written in python. One Bank Loan Fraud Detection is used in the proposed study.

4.1 WORKING

The set of rules or the algorithm which is being used in this research paper is mentioned below:

4.1.1 ALGORITHM

An algorithm is a well-defined collection of instructions for solving a certain issue. It accepts a collection of inputs and outputs the desired result.

START

STEP 1: Open the App.

STEP 2: Enter user account Number
STEP 3: Enter User Name

STEP 4: Select the Gender of User.

STEP 5: Select the marital Status.

STEP 6: Set No. of Dependents on User.

STEP 7: Select the Education qualification of User.
STEP 8: Enter User's Job status

STEP 9: Select the user Property area.

STEP 5: Select the Credit score.

STEP 6: Set User's monthly Income.

STEP 7: Set the user's co'Applicant Monthly Income.
STEP 8: Enter the loan Amount.

STEP 9: Select the duration of Loan.

STEP 10: Click on the submit button and wait for the result.

END

4.2 SENDER TO RECEIVER SMART CONTRACT

The bank loan Fraud detection in our proposed system consists of the following fields: 1. Gender

2. Education

3. Marrital status

4. Loand Amount

5. Credit History

6. Account Balance

7. Property Area

8. Credit History

9. Dependants

10. Self Employment Status
There are more factors also

We store all the information on a secure server and there's no too Personal information Related to the User Figure 2.1 shows the code of ML Classifier and Streamlit .

```
import streamlit as st
from PIL import Image
import pickle


model = pickle.load(open('./Model/ML_Model.pkl', 'rb'))

def run():
    img1 = Image.open('bank.png')
    img1 = img1.resize((156,145))
    st.image(img1,use_column_width=False)
    st.title("Bank Loan Prediction using Machine Learning")
    st.text("Hola KIETIANS!!!")

    ## Account No
    account_no = st.text_input('Account number')

    ## Full Name
```

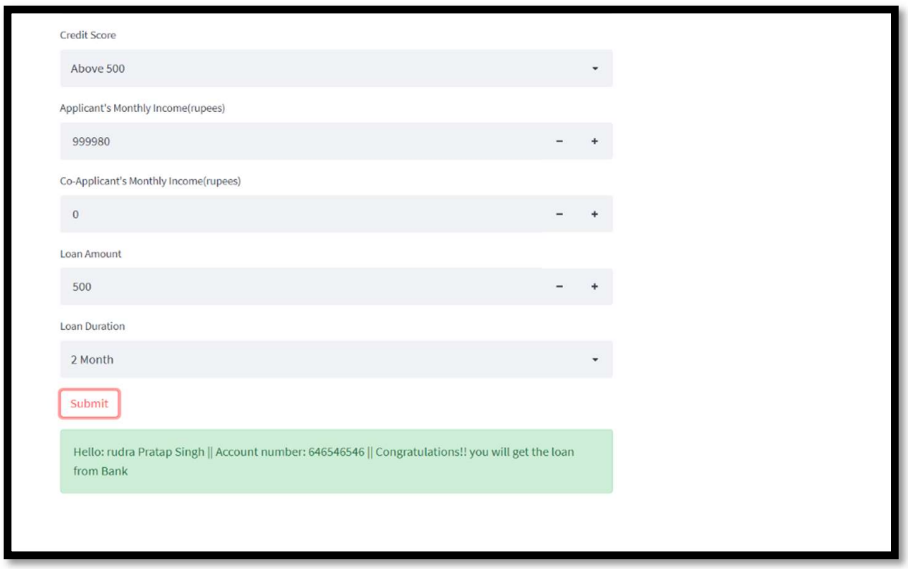
```
    fn = st.text_input('Full Name')

    ## For gender
    gen_display = ('Female','Male')
    gen_options = list(range(len(gen_display)))
    gen = st.selectbox("Gender",gen_options, format_func=lambda x:
gen_display[x])

    ## For Marital Status
    mar_display = ('No','Yes')
    mar_options = list(range(len(mar_display)))
    mar = st.selectbox("Marital Status", mar_options, format_func=lambda x:
mar_display[x])

    ## No of dependets
    dep_display = ('No','One','Two','More than Two')
    dep_options = list(range(len(dep_display)))
    dep = st.selectbox("Dependents",  dep_options, format_func=lambda x:
dep_display[x])

    ## For edu
    edu_display = ('Not Graduate','Graduate')
    edu_options = list(range(len(edu_display)))
    edu = st.selectbox("Education",edu_options, format_func=lambda x:
edu_display[x])

    ## For emp status
    emp_display = ('Job','Business')
    emp_options = list(range(len(emp_display)))
    emp = st.selectbox("Employment Status",emp_options, format_func=lambda x:
emp_display[x])

    ## For Property status
    prop_display = ('Rural','Semi-Urban','Urban')
    prop_options = list(range(len(prop_display)))
    prop = st.selectbox("Property Area",prop_options, format_func=lambda x:
prop_display[x])

    ## For Credit Score
    cred_display = ('Between 300 to 500','Above 500')
    cred_options = list(range(len(cred_display)))
    cred = st.selectbox("Credit Score",cred_options, format_func=lambda x:
cred_display[x])

    ## Applicant Monthly Income
```

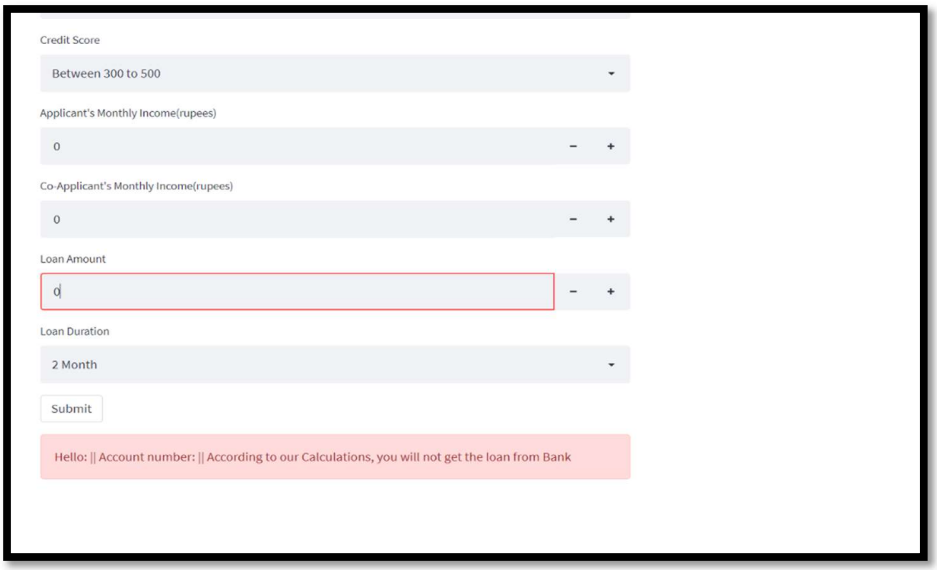
```
    mon_income = st.number_input("Applicant's Monthly
Income(rupees)",value=0)

    ## Co-Applicant Monthly Income
    co_mon_income = st.number_input("Co-Applicant's Monthly
Income(rupees)",value=0)

    ## Loan AMount
    loan_amt = st.number_input("Loan Amount",value=0)

    ## loan duration
    dur_display = ['2 Month','6 Month','8 Month','1 Year','16 Month']
    dur_options = range(len(dur_display))
    dur = st.selectbox("Loan Duration",dur_options, format_func=lambda x:
dur_display[x])

    if st.button("Submit"):
        duration = 0
        if dur == 0:
            duration = 60
        if dur == 1:
            duration = 180
        if dur == 2:
            duration = 240
        if dur == 3:
            duration = 360
        if dur == 4:
            duration = 480
        features = [[gen, mar, dep, edu, emp, mon_income, co_mon_income,
loan_amt, duration, cred, prop]]
        print(features)
        prediction = model.predict(features)
        lc = [str(i) for i in prediction]
        ans = int("".join(lc))
        if ans == 0:
            st.error(
                "Hello: " + fn +" || "
                "Account number: "+account_no +' || '
                'According to our Calculations, you will not get the loan
from Bank'
            )
        else:
            st.success(
                "Hello: " + fn +" || "
                "Account number: "+account_no +' || '
```

```
                'Congratulations!! you will get the loan from Bank'
            )

run()
```

Figure 4.3 Interface of Classifier

In the figure 4.4 Results based on the input is shown:





CHAPTER 5

SUSTAINABLE DEVELOPMENT GOALS

OVERVIEW

The Sustainable Development Goals (SDGs) or Global Goals are a set of 17 interconnected global goals intended to serve as a "roadmap to a better and more sustainable future for all."

The Joined together Countries Common Gathering (UN-GA) built up the SDGs in 2015, with the objective of accomplishing them by 2030. They are contained in a UN-GA Determination known as the 2030 Plan, some of the time known casually as Plan 2030. The SDGs were outlined as long-term worldwide advancement system to supersede the Thousand years Advancement Objectives, which were completed in 2015.

4.1 **The 17 Sustainability development goals**

4.2 **No Poverty**

Conclusion destitution in all its shapes all over

5 Zero Hunger

Conclusion starvation, accomplish nourishment security and moved forward sustenance and advance feasible horticulture.

5.1.3 **Good Health and Well-being**

Guarantee solid lives and advance well-being for all at all ages.

5.1.4 **Quality Education**

Guarantee comprehensive and even-handed quality instruction and advance long lasting learning openings for all.

5.1.5 **Gender Equality**

Accomplish sexual orientation quality and engage all ladies and young ladies.

5.1.6 **Clean Water and Sanitation**

Guarantee accessibility and economical administration of water and sanitation for all.

5.1.7 **Affordable and Clean Energy**

Guarantee get to to reasonable, dependable, economical and cutting edge vitality for all.

5.1.8 **Decent Work and Economic Growth**

Advance supported, comprehensive and maintainable financial development, full and beneficial business and better than average work for all.

5.1.9 **Industry, Innovation and Infrastructure**

Construct versatile framework, advance comprehensive and feasible industrialization and cultivate advancement.

5.1.10 **Reduced Inequality**

Diminish imbalance inside and among nations.

5.1.11 **Sustainable Cities and Communities**

Make cities and human settlements comprehensive, secure, strong and maintainable.

5.1.12 **Responsible Consumption and Production**

Guarantee maintainable utilization and generation designs.

5.1.13 **Climate Action**

Take critical activity to combat climate alter and its impacts.

5.1.14 **Life Below Water**

Preserve and reasonably utilize the seas, oceans and marine assets for maintainable improvement

5.1.15 **Life on Land**

Ensure, re-establish and advance economical utilize of earthbound biological systems, economically oversee woodlands, combat desertification, and end and invert arrive corruption and stop biodiversity misfortune.

5.1.16 **Peace and Justice Strong Institutions**

Advance serene and comprehensive social orders for maintainable advancement, give get to to equity for all and construct successful, responsible and comprehensive educate at all levels.

5.1.17 **Partnerships to achieve the Goal**

Reinforce the implies of usage and revitalize the worldwide organization for feasible improvement.

Figure 5.1 appears feasible advancement objectives.

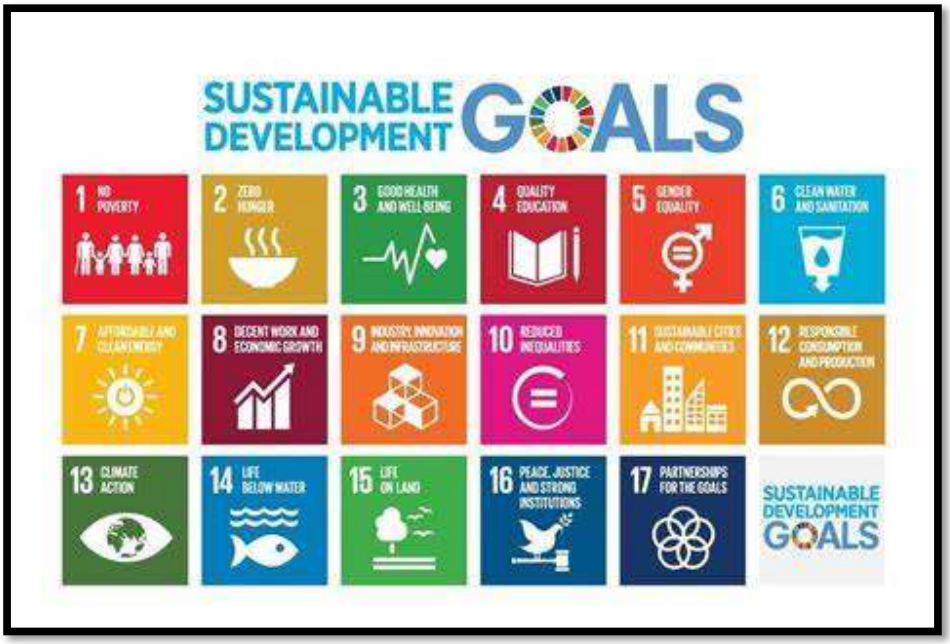


Figure 5.1: appears feasible advancement objectives

Our project focusses on the **ninth goal** of the UN Sustainable Goal which is "Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation".

5.2 The Ninth Goal

The targets which come under this goal are:

- Develop quality, reliable, sustainable and resilient infrastructure, including regional and transborder infrastructure, to support economic development and human well- being, with a focus on affordable and equitable access for all.
- Promote inclusive and sustainable industrialization and, by 2030, significantly raise industry's share of employment and gross domestic product, in line with national circumstances, and double its share in least developed countries.

- Increase the access of small-scale industrial and other enterprises, in particular in developing countries, to financial services, including affordable credit, and their integration into value chains and markets
- By 2030, upgrade infrastructure and retrofit industries to make them sustainable, with increased resource-use efficiency and greater adoption of clean and environmentally sound technologies and industrial processes, with all countries taking action in accordance with their respective capabilities
- Enhance scientific research, upgrade the technological capabilities of industrial sectors in all countries, in particular developing countries, including, by 2030, encouraging innovation and substantially increasing the number of research and development workers per 1 million people and public and private research and development spending
- Facilitate sustainable and resilient infrastructure development in developing countries through enhanced financial, technological and technical support to African countries, least developed countries, landlocked developing countries and small island developing States 18
- Support domestic technology development, research and innovation in developing countries, including by ensuring a conducive policy environment for, inter alia, industrial diversification and value addition to commodities
- Significantly increase access to information and communications technology and strive to provide universal and affordable access to the Internet in least developed countries by 2020

With our research, we wish to upgrade the technological capabilities of industrial sectors in all countries, in particular developing countries, including, by 2030, encouraging innovation and substantially increasing the number of research and development workers per 1 million people and public and private research and development spending.

CHAPTER 6

CONCLUSION

The major goal of this research paper is to show how Machine Learning can be used to create a more efficient and easier to use system, as well as how Machine Learning can be used in the field of research and Technology.

Machine Learning is a well-known technology that has aided in the resolution of a wide range of challenges in a variety of industries. It's a technology that's endless, transparent, and secure. Machine Learning is a potentially powerful and revolutionary technology since it reduces risk, eliminates fraud, and promotes transparency in a scalable manner for a wide range of applications. This technology uses consensus mechanisms for security purposes. The data is very critical component in the System and it is very important and it is used to train and test the machine learning model set.

In Machine Learning it’s nearly impossible to with the data as it is stored in a Machine Learning is used in a wide range of areas such as supply chain, healthcare, cryptocurrency exchange, banking, law enforcement, voting, internet of things, real estate, digital Ids, etc.

Machine Learning technology ensures that it can be implemented anywhere in any field. Limitations like third party involvement, delay in output process, Training Time, and much more which are associated with the current use cases.

The proposed system talks about the use of Machine Learning and its Algorithms, streamlit in Classifier.

In conclusion, Machine Learning have been successfully implemented, which aims to secure the entire process. The one-way process in the secure transmission of data to Authorities, who then use the Data to validate person Details based on the Provides documents with the database. The validated Users are subsequently placed in the further Process, where they cannot be tampered with once they have been stored. As a result, the application seeks to provide a safe online procedure by overcoming threats such as man-in-the-middle and eliminating third-parties, making the entire process of online and faster.

CHAPTER 7

FUTURE WORK

Future research will be devoted to the development of a user-friendly graphic user interface that will further improve the overall experience of the user as well as to explore the possibility of implementing the classifier in Banking System and other loan Providing Firms.

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