

KiRTi: A Blockchain-based Credit Recommender System for Financial Institutions

Submitted in partial fulfillment of the
requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering

By

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**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SCHOOL OF COMPUTING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade “A++” by NAAC

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Ajitha Sree.E (40110041)** and **Roshan .J(40111081)** who carried out the Project Phase-1 entitled “**KiRTi: A Blockchain-based Credit Recommender System for Financial Institutions**” under my supervision from June 2023 to Nvember 2023.

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DECLARATION

I, **Ajitha Sree. E(40110041)**, hereby declare that the Project Phase-1 Report entitled **“KiRTi: A Blockchain-based Credit Recommender System for Financial Institutions”** done by me under the guidance of **Dr.A.C.SANTHA SHEELA ,M.E.,Ph.D** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Computer Science and Engineering**.

DATE:

PLACE: Chennai

SIGNATURE OF THE CANDIDATE

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ABSTRACT

KiRTi, a deep-learningbased credit-recommender scheme for public blockchain to facilitate smart lending operations between prospective borrowers (PB) and prospective lenders (PL) to eliminate the need of third party credit-rating agencies (CRAs) for credit-score (CS) generation. Thus loan grants to PB from PL is secured, authorized, and automated so as to expedite the disbursement process. KiRTi stores PB historical transactions, current assets, and liabilities as time-series sequenced data in a public blockchain. The sequenced data is fetched from blockchain by a long-short term memory (LSTM) model that generates CS for loan recommendations based on proposed lending algorithms for PB and PL. To ensure real-time updation of CS, edge-weights are updated based on boolean indicators from PB and PL, which indicates the successful repayments and loan-defaults. The process is iterated to improve the accuracy of edge-weights and generated CS o ensures the correct credibility of PB for future lending. Smart contracts (SC) are proposed for automatic setup of loan repayments between PB and PL. To model the LSTM recommender scheme, a German credit dataset from UCI repository is considered with 1000 credit-histories of PB, with 700 successful repayments and 300 defaults. KiRTi achieves an accuracy of 97.5% in comparison to conventional approaches with an Fmeasure of 0.98304. The security evaluation of KiRTi shows that it has computation cost of 20.96 ms and communication cost of 121 bytes compared to other state-of-the-art approaches.

TABLE OF CONTENTS

CHAPTER No	TITLE	PAGE
	LIST OF FIGURES	Viii
1	INTRODUCTION	9
2	LITERATURE SURVEY	11
2.1	Inferences From Literature Survey	13
2.2	Open Problems in Existing System	13
2.3	Problem Statement	14
3	REQUIREMENTS SPECIFICATION	15
3.1	Hardware and Software Specification	15
3.2	Analysis Of The Project	15
4	DESCRIPTION OF PROPOSED SYSTEM	22
4.1	Selected Methodology Or Process model	22
4.2	Architecture/Overall Design Of Proposed System	23
4.3	Description Of Software For Implementation And Testing Plan Of The Proposed Module/System	25

4.4	Project Management Plan	27
5	CONCLUSION	28
	REFERENCES	29

LIST OF FIGURES

FIGURE NO	FIGURE NAME	PAGE NO
3.2.1.1	Java Programming Language	16
3.2.1.2	Java Programming Language	17
3.2.2	Java Platform	18
3.2.4	Blockchain	20
4.2	Architecture / Overall Design	23

CHAPTER 1

INTRODUCTION

In modern financial institutions, loan disbursement to PB by financial stakeholders like banks, insurance agencies, and PL are facilitated through electronic loan records. The records consists of PB sensitive information, such as their unique identification number, address, income-tax returns, and financial assets. PL shares the loan records to third-party CRAs that evaluate risk in granting loan to PB by generating a CS for PB. To generate CS, CRAs charge hefty amounts from PL that it enforces on PB once loan grants are finalized. CRAs forms recommender model on PB historical data of financial transactions that includes details like- age, loan purpose, previous credit and lending histories, nature of job, current assets and liabilities, and bank account balance to compute CS. To facilitate the same, recommender systems employ two set of filtering mechanisms on PB loan records- collaborative and content based filters. Collaborative filters analyze PB current assets and liabilities, job type (business/salaried), and age to determine risk in loan grants, whereas content filters analyzes PB previous repayments and defaults to compute a lending score. The risk values and lending scores goes through multiple iterations (cycles) of statistical inferences to finalize CS for PB. Based on CS, PL forms an informed decision on amount of loan grant, interest-rate fixation, and repayment period of the granted loan. The current loan recommender models are complex, and the overall loan disbursement cycle is slow and tedious in nature. This is due to complex co-relations that exist among diverse set of parameters like- previous credit histories, defaults, and length of repayment cycles. Also, loan grants are subjective to PL profit margins, with different levels of uncertainty, depending on PL prospective. For some PL, loss (defaults) are more critical than gains (repayments), and vice-versa. Thus, the recommender models might assign different scores to same PB, which results in the proportionality of the assessed risk by PL. This approach is flawed as even a missed repayment can affect CS resulting in the calculation of high risk. Also, CS generated through recommender models does not take into account new PB having a good reputation and high assets as their credit histories are absent. This assigns low CS to new PB, which effects future lending scope of such PB. Apart from complexity of recommender models, credit repositories of PB are stored in central servers and are subject to privacy and security issues. CRAs, PL and other financial stakeholders like insurance agencies, and banks,

fetches PB sensitive information from these repositories using an open unsecured channels, i.e., the Internet [1]. Thus, any malicious intruder can also gain access to these repositories, which raises security concerns like identity theft, selling of PB records for personal motives, and data breaches. As per the reports of the Federal Trade Commission, 148 million customers data was breached at Equifax, one of the largest CRAs in the United States, amounting to \$425 billion loss to the industry [2]. According to United States InfoSearch, Experian databases were also breached by running malicious service daemons on workstations that allowed identity theft of 200 million consumer records, with the loss approximated close to \$1.3 billion to the CRA [3].

CHAPTER 2

LITERATURE SURVEY

Blockchain being considered as a pioneering technology in present era solves a multitude of problems that require the sense of privacy, security, validity, and pseudo-anonymity of the transactions. Therefore, after Blockchain which grew into much affluence led to a tremendous disruption in the financial sector where the primary concern of the individuals lies on the fact of handling the transaction level data securely. In this , two different types of credit scoring system have been proposed where one belongs to the scoring of the credit of an individual, which can be used by the individual to pursue loans or credit invoices.

Financial risk management is one of the most sensitive subjects that should be taken into account several important factors. Bank industry includes many types of risk affecting both banks and their customers. Credit scoring (CS) has a close relationship to banks being an effective and crucial approach for analyzing the borrowing and lending of money. Lending money is risky but at the same time, is a very crucial source of income for banks, investors, and financiers. To minimize the risk of lending and to calculate the probability of a borrower of becoming delinquent, the most common method being used since the 1950s is credit scoring. This method of calculating a credit score is based on some statistical analysis of historical data, which is very common in lending.

The remainder of this paper is organized as follows: Section 2 provides an overview of related work in the field of efficient financial systems in credit analysis. Section 3 details Credit risk assessment model for small and micro-Enterprises: The case of Lithuania. Section 4 details DGHNL: A new deep genetic hierarchical network of learners for prediction of credit scoring. Drilling into Dashboards: Responding to computer Recommendation in Fraud Analysis in Section 5, followed by conclusion and secure lending in Section 6 .

The authors, Sabyasachi Chakraborty and Satyabrata Aich proposed A Blockchain based Credit Analysis Framework for Efficient Financial Systems where Blockchain technology has significantly disrupted the credit industry, particularly in credit cards and financial supply chain management. The credit card-based system is complex and requires significant processing and validation charges. Financial organizations must verify customers' pay term history, CIBIL Score,

and capability to pay out credit funds. The credit system in Financial Supply Chain Management (FSCM) is one of the toughest to manage, with dynamic credit exposure and time-consuming analysis. A blockchain-based environment can assess customer eligibility and calculate credit scores based on consensus among stakeholders like banks, insurance agencies, and third-party financial organizations. This makes a blockchain-based credit analysis framework useful for gathering information about customers from multiple financial sectors.

The work of the authors, Rasa Kanapickiene and Renatas Spicas proposed the research aims to create a statistical enterprise trade credit risk assessment (ETCRA) model for Lithuanian small and micro-enterprises (SMiE). The model uses financial and non-financial data from 734 enterprises between 2010-2012. It assesses the enterprise's financial performance from different perspectives, including profitability, liquidity, solvency, and activity. The model can be used for both financial ratios and non-financial variables, and can be used by suppliers when making trade credit decisions for SMiE. The developed models can help suppliers manage insolvency risks.

The authors, Pawel Plawiak and Moloud Abdar proposed Credit scoring (CS) is crucial for risk management in banks and financial institutions. A new methodology, Deep Genetic Hierarchical Network of Learners (DGHNL), is introduced, incorporating various types of learners such as Support Vector Machines (SVM), k-Nearest Neighbors (kNN), Probabilistic Neural Networks (PNN), and fuzzy systems. The model uses the Statlog German credit approval dataset and applies deep learning, ensemble learning, supervised training, layered learning, genetic selection of features, genetic optimization of learners parameters, and genetic layered training approaches. The model achieves a prediction accuracy of 94.60%.

In this work, the authors, Natan Morar, Chris Baber and Faye McCabe , proposed Credit card fraud analysis is largely automated, but human analysts may intervene in situations where a transaction triggers an automated alert. Automated analysis recommends a fraud pattern, and a dashboard is used to support the analyst. The efficiency of people responding to the computer's recommendation is studied, focusing on information search efficiency. Results show that participants adapt their decision-making to the automated support's confidence and are efficient in time spent looking at relevant information.

The authors, Vikas Hassija and Gaurang Bansal proposed Credit scoring is a statistical analysis used by lenders to assess an individual's creditworthiness. However, it's a tedious task based on transaction records and professional background. This paper proposes a blockchain-based solution for decentralized credit scoring evaluation, reducing paperwork dependence. The paper uses prospect theory to model optimal investment strategies for different risk-return scenarios.

2.1 INFERNCE FROM LITERATURE SURVEY

The authors propose a blockchain-based credit analysis framework for efficient financial systems, addressing the challenges of managing credit cards and financial supply chain management. They propose a model for Lithuanian small and micro-enterprises, using financial and non-financial data from 734 enterprises between 2010-2012. The model helps suppliers manage insolvency risks and achieves a prediction accuracy of 94.60%.

The authors also introduce a new methodology for credit scoring, using Deep Genetic Hierarchical Network of Learners (DGHNL), which achieves a prediction accuracy of 94.60%. They also study the efficiency of human analysts in automated credit card fraud analysis, focusing on information search efficiency. The authors propose a blockchain-based solution for decentralized credit scoring evaluation, reducing paperwork dependence and modeling optimal investment strategies for different risk-return scenarios.

This model offers advantages in terms of credit analysis and fraud analysis, there are challenges related to credit analysis, credit card fraud analysis and credit scoring. Careful consideration and experimentation are essential for optimizing the model's performance and addressing potential limitations.

2.2 OPEN PROBLEMS IN EXISTING SYSTEM

The financial details and transaction statements of a customer are stored in centralized systems, which can lead to system failures and setbacks for organizations. Micro-enterprises struggle with drawing up notes and cash flow ratios. A layered learning approach, similar to deep learning, progresses differently in different situations. This approach can be used for transactions in geographically remote places. Lending money is risky but crucial for banks, investors, and financiers.

The system holds customer financial details and transaction statements, but centralized systems can cause system failures. Micro-enterprises struggle with drawing up notes and cannot calculate cash flow ratios due to the limited set of financial statements.

A layered learning approach, similar to deep learning, involves a variety of learners performing preprocessing, feature extraction, and connections. It resembles neurons in the neocortex of the brain. It considers situations where automated alerts are not sufficient, such as increased spending on a single card or transactions in remote locations.

Automated alerts may be triggered in situations like increasing card spending or transactions in remote locations. Lending money is risky but crucial for banks, investors, and financiers, as it is a crucial source of income.

2.3 PROBLEM STATEMENT

The financial details and transaction statements of a customer are stored in centralized systems, which can lead to system failures and setbacks for organizations. Micro-enterprises struggle with drawing up notes and cash flow ratios. A layered learning approach, similar to deep learning, progresses differently in different situations. This approach can be used for transactions in geographically remote places. Lending money is risky but crucial for banks, investors, and financiers.

SOLUTION

1. Blockchain Integration.
2. Smart Contracts for credit Agreements.
3. Decentralized consensus Mechanism.
4. Data privacy measures.
5. Integration with Traditional credit scoring models.
6. Immutable credit history records.
7. Real-time monitoring and Reporting.
8. User Education and Adoption.

CHAPTER 3

REQUIREMENT SPECIFICATIONS

3.1 HARDWARE AND SOFTWARE SPECIFICATION

3.1.1 HARDWARE REQUIREMENTS

- Hard Disk : 80GB and Above
- RAM : 4GB and Above
- Processor : P IV and Above

3.1.2 SOFTWARE REQUIREMENTS

- Windows 7 and above(64 bit)
- JDK 1.8
- Python 3.6.3
- Tomcat 9.0.26
- MySQL

3.2 ANALYSIS OF THE PROJECT

3.2.1 JAVA PROGRAMMING LANGUAGE

Java is unusual in that each Java program is both compiled and interpreted. With a compiler, you translate a Java program into an intermediate language called **Java byte codes** – the platform independent codes interpreted by the Java interpreter. With an interpreter, each Java byte code instruction is parsed and run on the computer. Compilation happens just once; interpretation occurs each time the program is executed. This figure illustrates how it works:

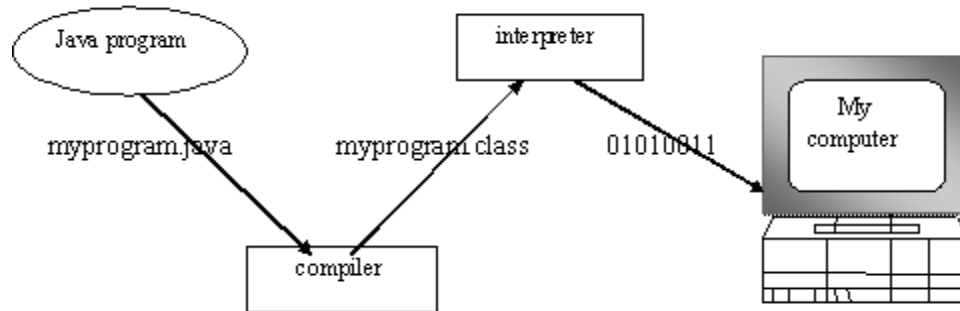


Fig.3.2.1.1 Java Programming Language

You can think of Java byte codes as the machine code instructions for the **Java Virtual Machine (JVM)**. Every Java interpreter, whether it's a Java development tool or a Web browser that can run Java applets, is an implementation of JVM. That JVM can also be implemented in hardware. Java byte codes help make “write once, run anywhere” possible.

You can compile your Java program into byte codes on any platform that has a Java compiler. The byte codes can then be run on any implementation of the JVM. For example, that same Java program can be run on Windows NT, Solaris and Macintosh.

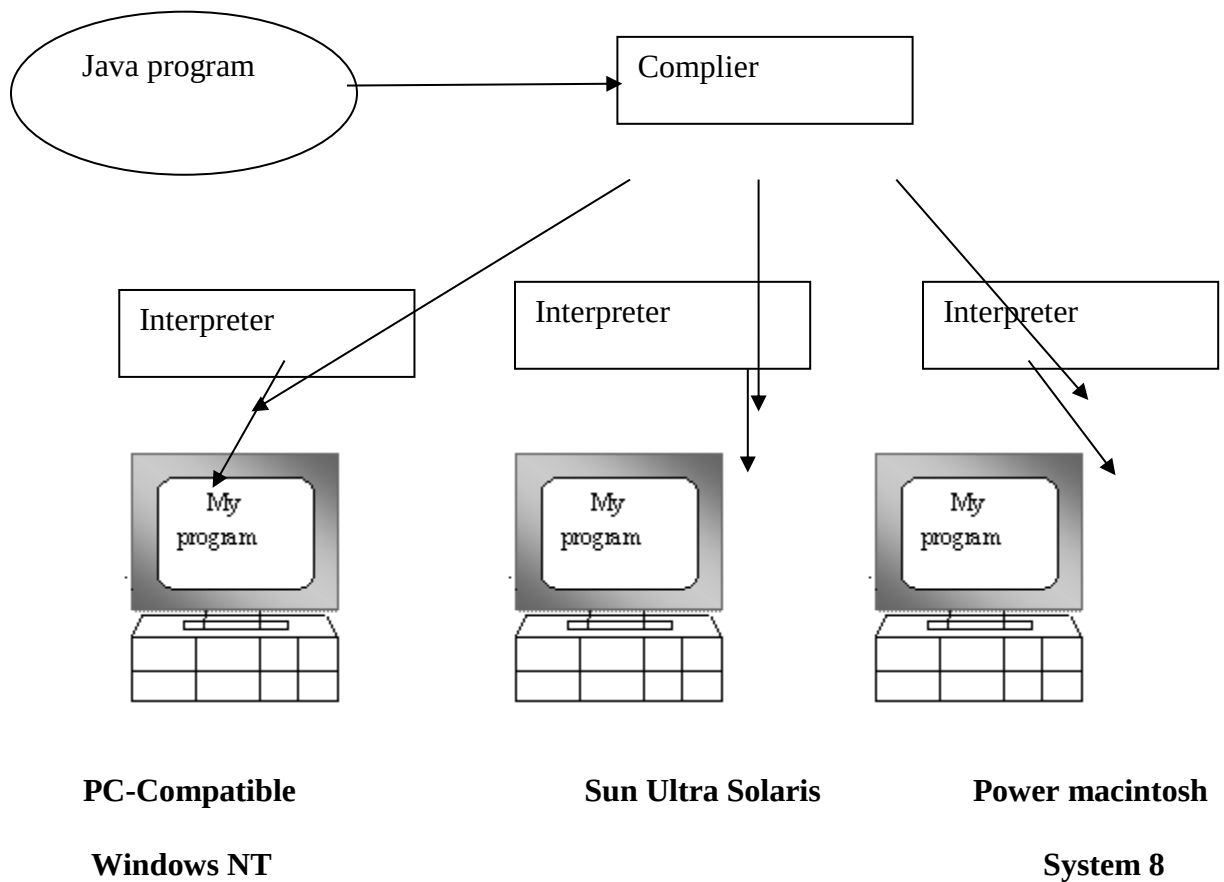


Fig.3.2.1.2 Java Programming Language

3.2.2 JAVA PLATFORM

A platform is the hardware or software environment in which a program runs. The Java platform differs from most other platforms in that it's a software-only platform that runs on top of other, hardware-based platforms. Most other platforms are described as a combination of hardware and operating system.

The Java platform has two components :

- The Java Virtual Machine (JVM)
- The Java Application Programming Interface (Java API)

You've already been introduced to the JVM. It's the base for the Java platform and is ported onto various hardware-based platforms.

The Java API is a large collection of ready-made software components that provide many useful capabilities, such as graphical user interface (GUI) widgets. The Java API is grouped into libraries (**packages**) of related components. The following figure depicts a Java program, such as an application or applet, that's running on the Java platform. As the figure shows, the Java API and Virtual Machine insulates the Java program from hardware dependencies.

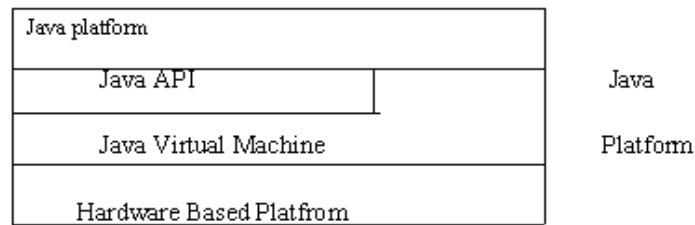


Fig.3.2.2 Java Platform

As a platform-independent environment, Java can be a bit slower than native code. However, smart compilers, weel-tuned interpreters, and just-in-time byte compilers can bring Java's performance close to that of native code without threatening portability.

3.2.3 APACHE TOMCAT SERVER

Apache Tomcat (formerly under the Apache Jakarta Project; Tomcat is now a top level project) is a web container developed at the Apache Software Foundation. Tomcat implements the servlet and the JavaServer Pages (JSP) specifications from Sun Microsystems, providing an environment for Java code to run in cooperation with a web server. It adds tools for configuration

and management but can also be configured by editing configuration files that are normally XML-formatted. Because Tomcat includes its own HTTP server internally, it is also considered a standalone web server.

3.2.4 Introduction to Blockchain

With the emergence of Digital Currency (aka Crypto currency), several enterprises or financial institutions are experimenting with the Distributed Ledger system as a trusted way to track the ownership of the assets without any central authority.

The core system behind the new currency system is Blockchain technology. A walkthrough of the basic building blocks of the Blockchain technology is described below. A Blockchain is basically a chain of Blocks. Blocks are hashed using SHA-256 hashing algorithm to generate the signature of the data associated with it.

One way to fix it is to run mining and recalculate the Hash value of Block #1 which basically will generate new value for Nonce and hence leading to a valid Hash value which starts with 4 zeroes. Copying this to next Block #2's Prev field will fix these 2 Blocks. However in order to fix the whole Blockchain, we need to continue with this process for all the Blocks in the chain so that all Blocks point to new & valid Hash codes of their previous blocks.

The cost of fixing the tampered Blockchain as described in above process is very high. Because we have to go and fix the Chain from the starting Block to the last one. In case the Chain is large, it becomes costly operation. In case of Distributed Blockchain where several Peers are involved in the process and keeping the copy of the Blockchain, the repairing the Blocks becomes even more costly operation.

The other and more efficient process is to come up with the compensating data and add this Block at the end of the Chain. E.g. In case your Chain contains the financial transaction (money movement) in Data field of the Block, then instead of fixing each of the Block's Data with corrected financial transaction, come up with the adjusted financial transaction (aka compensating transaction) and create a Block (with Data=adjusted transaction record) and add this Block to the Blockchain (adds to the end of the Chain).

SHA256 Hash

Data:	test data
Hash:	916f0027a575074ce72a331777c3478d6513f786a591bd892da1a577bf2335f9

Block

Block:	# 1
Nonce:	72608
Data:	
Hash:	0000f727854b50bb95c054b39c1fe5c92e5ebcfa4bcb5dc279f56aa96a365e5a
Mine	

Blockchain

Block: # 1

Nonce: 20839

Data: test data 1

Prev: 00

Hash: 00002a70c8d0034addeab115689ba9e79c8b8dbbd81b083be396c199bf

Mine

Block: # 2

Nonce: 81984

Data: test data 2

Prev: 00002a70c8d0034addeab115689ba9e79c8b8dbbd81b083be396c199bf

Hash: 0000a97e44b78fba8baabc2523d45e4a3cec092af26b185f29cd1336c94e

Mine

Block: # 3

Nonce: 79796

Data: test data 3

Prev: 0000a97e44b78fba8baabc2523d45e4a3cec092af26b185f29cd1336c94e

Hash: 0000f2926342c369daff2bcc3fdad34f792

Mine

Fig.3.2.4 Blockchain

CHAPTER 4

DESCRIPTION OF PROPOSED SYSTEM

In existing system, the overall loan disbursement cycle is slow and tedious in nature. This is due to complex co-relations that exist among diverse set of parameters like- previous credit histories, defaults, and length of repayment cycles. Also, loan grants are subjective to PL profit margins, with different levels of uncertainty, depending on PL prospective. For some PL, loss (defaults) is more critical than gains (repayments), and vice-versa. Thus, the recommender models might assign different scores to same PB, which results in the proportionality of the assessed risk by PL. This approach is flawed as even a missed repayment can affect CS resulting in the calculation of high risk. Also, CS generated through recommender models does not take into account new PB having a good reputation and high assets as their credit histories are absent.

In proposed System, loan disbursement cycle is high. Perspective lenders and perspective borrowers have direct communication. So, that they can know their details clearly. In this approach we implement a sentiment analysis to read a borrowers reviews. For using sentiment analysis we can find out the total percentage of positive reviews negative reviews. Based on the reviews and positive negative reviews percentage PL will decide to lend the loan to that particular user or not. So that maximum users can get a loan without any difficulties. We will store the perspective lender lending details and perspective borrower's payment history in block-chain.

Advantage

- ✓ Every perspective borrower has a possibility to get a loan from lender.
- ✓ Perspective lenders and perspective borrowers had to know each other's identity.

4.1 SELECTED METHODOLOGY OR PROCESS MODEL

Smart lending operations in modern financial institutions are based on recommender models to generate CS to facilitate loan grants to PB. To ensure credibility in generation of CS, and transparency in evaluation of loan grants, the proposed scheme KiRTi integrates blockchain and deep-learning to facilitate a trust based recommender ecosystem. In KiRTi, LSTM model is

applied to ensure accurate predictions on PB historical repositories and blockchain offers immutability in stored records. To improve the decision analytics over time, and minimize bias, a feedback system is evolved that updates edge-weights of LSTM in real-time, so CS are accurate and up-to-date. SC necessitates automated re-payments from PB to PL. The proposed results indicate the efficacy of the scheme against existing credit schemes. However, the LSTM model operates on feedbacks to update CS that induce latency overheads.

4.2 ARCHITECTURE / OVERALL DESIGN OF PROPOSED SYSTEM

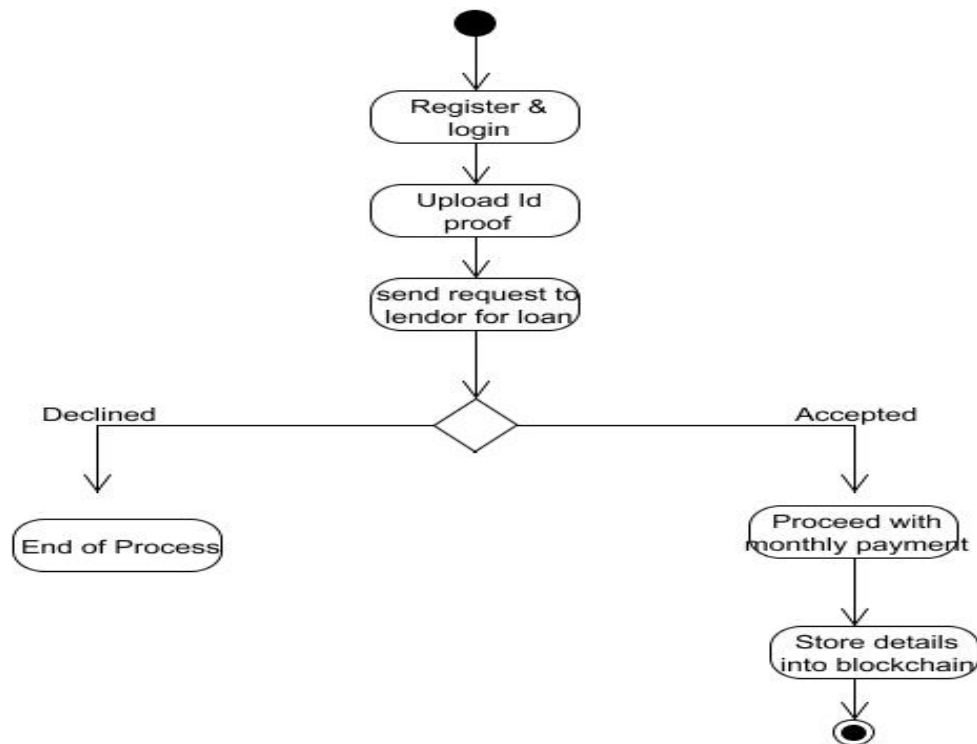


Fig 4.2.1 Overall Design

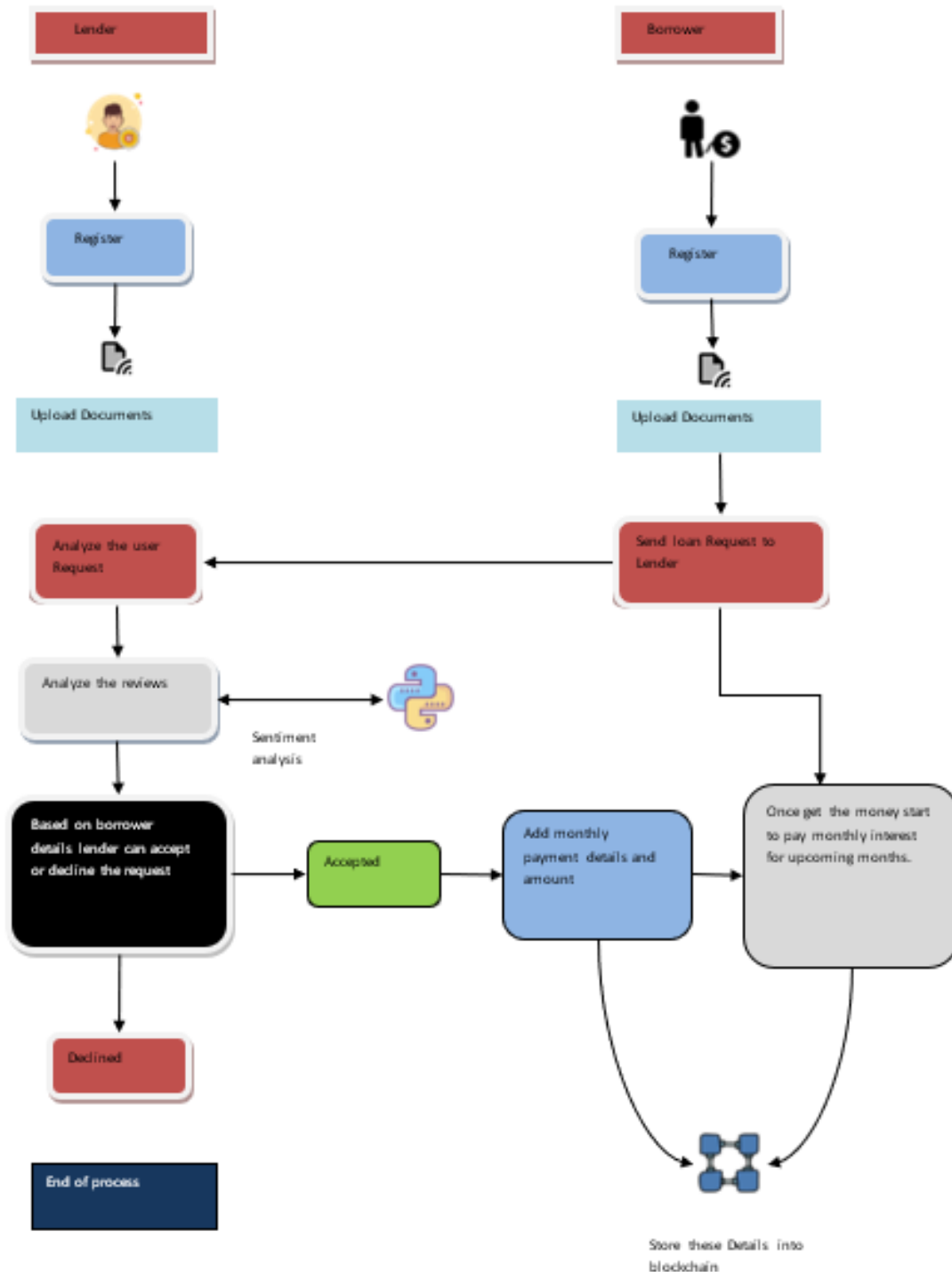


Fig.4.2.2 System Architecture

4.3 DESCRIPTION OF SOFTWARE FOR IMPLEMENTATION AND TESTING PLAN OF THE PROPOSED MODULE/SYSTEM

A hierarchical structuring of relations may result in more classes and a more complicated structure to implement. Therefore it is advisable to transform the hierarchical relation structure to a simpler structure such as a classical flat one. It is rather straightforward to transform the developed hierarchical model into a bipartite, flat model, consisting of classes on the one hand and flat relations on the other. Flat relations are preferred at the design level for reasons of simplicity and implementation ease. There is no identity or functionality associated with a flat relation. A flat relation corresponds with the relation concept of entity-relationship modeling and many object oriented methods.

The application at this side controls and communicates with the following three main general components.

- embedded browser in charge of the navigation and accessing to the web service;
- Server Tier: The server side contains the main parts of the functionality of the proposed architecture. The components at this tier are the following.

Web Server, Security Module, Server-Side Capturing Engine, Preprocessing Engine, Database System, Verification Engine, Output Module.

In proposed System, loan disbursement cycle is high. Perspective lenders and perspective borrowers have direct communication. So that they can know their details clearly. In this approach we implement a sentiment analysis to read a borrowers reviews. For using sentiment analysis we can find out the total percentage of positive reviews and negative reviews. Based on the reviews and positive negative reviews percentage PL will decide to lend the loan to that particular user or not. So that maximum users can get a loan without any difficulties. We will store the perspective lender lending details and perspective borrower's payment history in block-chain.

4.3.1 MODULES

- ❖ PB and PL Registration
- ❖ Loan Request by PB
- ❖ Sentiment Analysis
- ❖ Payment Tracking

4.3.2 MODULE DESCRIPTION

4.3.2.1 PB and PL Registration

In first module, Perspective lender and perspective borrower will register their personal information as well as income details. And also they will upload government issued documents for registration process.

4.3.2.2 Loan Request by PB

In second module when Perspective borrower login the registered perspective lenders details will shown as list. Borrower can choose the lender and he can check the lenders personal details and government Id proofs. Then he can send the request to the lenders. One PB should send request to one PL only.

4.3.2.3 Sentiment Analysis

In third module the requester borrower's details will be list down in lenders side. Lender can check borrower's personal info id proofs. Once he checked with the basic steps he will move on to sentiment analysis. Lender can check the positive reviews percentage, negative reviews percentage by using sentiment analysis.

4.3.2.4 Payment Tracking

In final module the borrower's monthly payment will be stored in block-chain. So that lenders can know about the date of payment and whether it is late payment or on time payment.

4.4 PROJECT MANAGEMENT PLAN

Loan disbursement cycle is high. Perspective lenders and perspective borrowers have direct communication. So that they can know their details clearly. In this approach we implement a sentiment analysis to read a borrowers reviews. For using sentiment analysis we can find out the total percentage of positive reviews and negative reviews. Based on the reviews and positive negative reviews percentage PL will decide to lend the loan to that particular user or not. So that maximum users can get a loan without any difficulties. We will store the perspective lender lending details and perspective borrower's payment history in block-chain. Every perspective borrower has a possibility to get a loan from lender. Perspective lenders and perspective borrowers had to know each other's identity.

August	Literature Survey
September	Data Acquisition
October	Data Preprocessing
November	Training and Splitting
December	Loading, training and testing the model
January	Predicting the output and generating the final report

CHAPTER 5

CONCLUSION

Smart lending operations in modern financial institutions are based on recommender models to generate CS to facilitate loan grants to PB. To ensure credibility in generation of CS, and transparency in evaluation of loan grants, the proposed scheme KiRTi integrates blockchain and deep-learning to facilitate a trust based recommender ecosystem. In KiRTi, LSTM model is applied to ensure accurate predictions on PB historical repositories and blockchain offers immutability in stored records. To improve the decision analytics over time, and minimize bias, a feedback system is evolved that updates edge-weights of LSTM in real-time, so CS are accurate and up-to-date. SC necessitates automated re-payments from PB to PL. The proposed results indicate the efficacy of the scheme against existing credit schemes. However, the LSTM model operates on feedbacks to update CS that induce latency overheads.

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