IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

AGRICULTURAL LOAN RECOMMENDER SYSTEM

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Abstract: The agricultural sector in India, where land ownership is frequently dispersed among many people and hinders industry growth, depends heavily on agricultural loans to remain operational. By using the K-nearest neighbor and fuzzy logic method to create an agricultural loan recommender system, this research offers a workable solution. With the technology, farmers can obtain customized loan recommendations in addition to statistical and graphical data relevant to agricultural loans. By using this approach, farmers may choose the best bank to apply to for loans based on their specific needs and have a greater grasp of the loan application process. The effectiveness of the suggested system is assessed, especially with regard to the likelihood of a bank recommending the requested loan amount.

Keywords - bank data, loanee data, agricultural loans, classifiers, data pre- processing.

I. Introduction

Agricultural finance is integral to the success of the agricultural industry. However, the current system often leaves many farmers in precarious financial situations, resulting in debt traps due to their limited understanding of agricultural finance. A significant gap exists between farmers seeking financial services and the banks providing them. The situation is exacerbated as impoverished farmers often turn to informal sources of credit, such as relatives or loan sharks, due to their ineligibility for bank loans. Relying on informal credit exacerbates their financial difficulties, as they must repay debts without the structured procedures offered by formal institutions. This cycle of debt undermines the effectiveness of the overall agricultural finance sector, impacting both the private and public sectors.

To address these challenges, this paper proposes a system for processing agricultural loan datasets. By utilizing statistical data, this system aims to draw relevant inferences and observations regarding the suitability of loan schemes for farmers' needs and banks' positions. The objective is to provide farmers and loan applicants with recommendations on the most suitable banks for their loan applications, based on observable patterns and specified requirements in the loan data.

II. EXISTING SYSTEM

Most of the farmers face the initial problem of agriculture is money. They are seeking to apply the loan for crop, but it's not an easy process to get an amount. The traditional loan management is time-consuming and requires collecting and verifying information about applicants, their trust worthiness and their creditability. Another problem is Corruption in purchase system is widespread because the huge amount involved and the presence of a large number of PACS makes it difficult to monitor the working of the scheme and leaves scope for leakages. Diversion of funds occurs at all levels - during procurement, movement of commodities between government warehouses, storage, and transport to FPSs.

III. PROPOSED SYSTEM

Agricultural loan waiver in India in terms of different analyses. The concept of farm loan waivers plays an important role in the approach of certain requirements. The distress of farmers rationalizes the concept of research in terms of suitable analysis. The financial statuses of the loan are especially occurring in the strategy of loan waivers. This article reviews the function of data on the concept of different methods in terms of suitable functions.

There is a wide range of circumstances in the approach of suitable functions. It identifies the possibility of the system on the basis of different assurance of loan products.

- We are going to develop an application for online multi-crop procurement and loan system.
- Farmers who need the loan for cultivation, they upload their details in the app.
- Also they choose the repay mode of the loan during the registration period.
- After the period of cultivation they get a amount or the crop by the respective farmers.
- Farmers also register the procurement through online.
- These details are monitored by the respective officers, and they get the crops from the farmers in the DPC‟‟s.

III AGRICULTURAL LOAN RECOMMENDER

The system comprises three primary procedures. Initially, the data, which in this study is exclusively focused on Shimoga, Karnataka, is pre-processed and graphically analyzed. Subsequently, the data is utilized to train the KNN Classifier, which offers the user the most suitable bank to meet their requirements. The preference for the KNN classifier over other classifiers is attributed to its speed and effectiveness . Lastly, the user's information and the outcome are stored in a database for future querying and transmission to individual banks for potential customers.

Figure 1 illustrates the activity diagram of the system, showcasing how it utilizes user input (in this case, the loan amount) and the KNN classifier to recommend a bank.

A. Data Pre-processing and Analysis

The Agricultural Loan Data for 2017 is collected from a website managed by the state government of Karnataka, India [6], which provides two distinct datasets: Individual Bank Data on Agricultural Loans and Individual Agricultural Loanee Data.

A.1. Bank Data

The bank data encompasses numerous features such as bank details, loan amount, and amount released by the bank, many of which are irrelevant to the paper's objective. Therefore, after preprocessing the data using Data frames loaded by Pandas [10], only the fields outlined in Table I are utilized for data analysis.

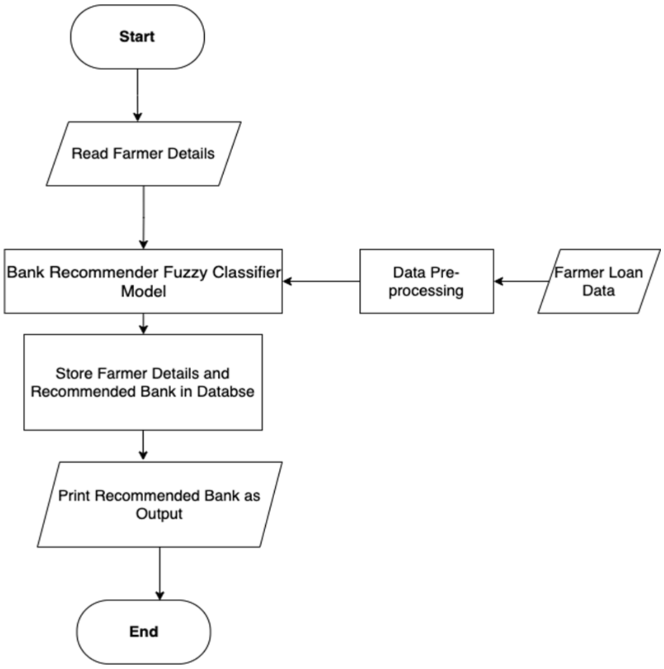

Fig 1: Work Flow Diagram

A.2. Loanee Data

The dataset containing Loanee details includes various data such as bank details, loan amount, green list, and amount released by the bank, many of which are not utilized by the system for computations and functions. After loading the data into a Data Frame, preprocessing is performed, while personal details of farmers are excluded to safeguard privacy.

The data is initially processed to filter out farmers who are not on the green list, meaning their loans did not get sanctioned. The resulting information is visually represented in Figure 2, a Pie Chart illustrating loan rejection reasons. This chart offers users insights into factors to consider before applying for an agricultural loan.

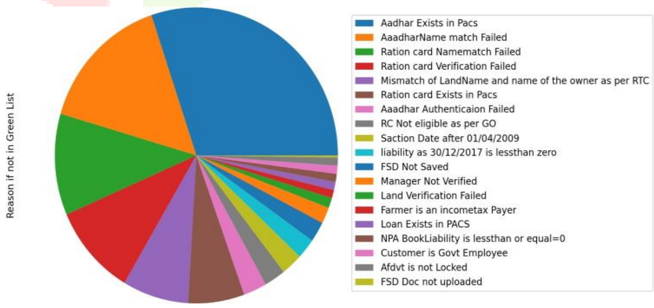

Fig 2: Pie Chart for Loan Rejection Reasons

B. KNN Classifier

A supervised KNN Classifier is employed for this task. The data is inputted into the Classifier, utilizing the Scikit Library [11], to train the model for recommending users to a bank that is best suited to meet their needs. The dataset is divided into a training set and a validation set in a 75:25 ratio. The algorithm requires only the loan amount requested by the user as input.

B.1. Feature Selection

Based on the provided data, certain columns contain personal information about farmers, rendering them unsuitable as features for classification. Therefore, entries whose loans have been cancelled are excluded from the dataset for classification purposes. The primary feature utilized for this classification is the Loan Amount as of 31-12-2017, as it exhibits a significantly low p-value. Other available features possess higher p-values, indicating acceptance of the null hypothesis.

B.2. Nearest Neighbors

The classifier utilizes fifty of the nearest neighbors to the input for determining the final output. This number is deemed optimal, as increasing the number of neighbors does not significantly impact the output.

B.3. Weights

Individual neighbors are weighted based on their distance from the input point. The classifier assigns weights to each calculated value based on their distances, with closer neighbors receiving higher weights. This approach helps refine the output and improve accuracy, particularly when dealing with outlier inputs.

B.4. Nearest Neighbor Algorithm

The KD Tree algorithm partitions the points into two child nodes from the parent node, using the median of the data as the root node. This process is recursively applied to subsequent nodes until all nodes are exhausted. This algorithm enhances efficiency, offering a better time complexity compared to the brute force algorithm, which is set by default.

B.5. Probability of Total Disbursement (without installments)

Following the classification of the most suitable bank for meeting the farmer's needs, the probability of the entire loan amount being disbursed is computed by dividing the total disbursements by the number of accepted loans.

c. Database

An SQLite Database is employed to store user inputs, including farmer details, and the predicted output of the classifier. Table III illustrates the schema of the database.

IV METHODOLOGY

a) Requirement Analysis and Planning:

Stakeholder Identification: Identify key stakeholders including farmers, financial institutions, and agricultural experts. Conduct surveys, interviews, and workshops to gather comprehensive requirements from stakeholders.

b) Data Collection and Preprocessing:

Data Gathering: Collect relevant data such as historical loan data, crop yields, weather patterns, market prices, and socio-economic factors from credible sources.

Preprocessing: Handle missing values, outliers, and inconsistencies in the data to ensure its quality and reliability.

c) User Interface Design:

Design a user-friendly web interface tailored to the needs of farmers and financial institutions. Develop input forms for farmers to provide information such as agricultural practices, land details, and loan requirements. Incorporate visualizations to display loan recommendations generated by the system, along with explanations of the decision process.

Provide interactive elements for users to adjust input parameters and see how loan recommendations change.

d) Integration and Deployment:

Integrate the trained model with the web interface. Develop backend functionalities for data processing, model inference, and user authentication. Deploy the Agricultural Loan Recommender System on a web server, ensuring scalability and security.

e) Quality Control and Testing:

In order to find and fix any problems or difficulties, thoroughly test the system. To make sure the system satisfies requirements and operates as intended, do quality assurance tests .For more advancements, get input from stakeholders and users.

f) Upkeep & Updates:

Keep an eye out for security flaws and system performance degradation on a regular basis. To keep the model accurate and relevant, periodically retrain it using new data that is added to the system.

Apply updates or new features in response to user comments and changing farming methods.

V RESULTS

The KNN Classifier has a validation accuracy of 68.67% based on the configuration and provides the following output.The output predicted by the KNN classifier while testing is shown in Table IV, including the probabilities of total amountdisbursement without instalments.

Here, the dominance of "Pragathi Gramin Krishna Bank" can be explained by the statistical analysis provided earlier; the number of loans sanctioned by the aforesaid bank is high till Rs. 4,00,000 and can be expected as a common recommendation.

The lack of correlation amongst the variety of features in the data has limited the potential of the classifier to a certain extent, but it still succeeds to provide a relevant output based on statistics. Inclusion of more relevant features would further increase the efficiency of the algorithm

The general scenario of agricultural finance suffers from a lack of proper connectivity between the loanee and the institutions providing financial support. The objective of the project was to take a machine learning-oriented approach to fix the disconnect between banks and loanees by providing the loanee with recommendations based on ML inferences made from loan datasets.

Hence, this project has the potential to act as a means of preparing the loanee for applying for an agricultural loan in a well-informed manner. This stands to help them improve their chances of having their loans sanctioned. Although the current overall accuracy of the recommendation is 68.67%, with more specific and vast datasets, this approach to building a loan recommendation system can be refined to give improved results that might even take into consideration more factors.

VI CONCLUSION

In the agricultural finance domain, a notable gap persists between loan applicants and supportive financial institutions. To address this issue, our project aimed to employ a machine learning-based strategy. By analyzing loan datasets, we sought to offer personalized recommendations to applicants, empowering them to make better-informed decisions when seeking agricultural loans. This endeavor holds promise in equipping applicants with the necessary insights to increase their chances of loan approval. Although the current recommendation accuracy stands at 68.67%, there is considerable room for improvement. With access to more extensive and specific datasets, we anticipate refining our approach to deliver enhanced outcomes, potentially considering a broader range of factors in the decision-making process.

Moreover, the implementation of our system extends beyond individual applicants. By streamlining the loan application process and bolstering approval rates, financial institutions stand to benefit from reduced risk and enhanced operational efficiency. Additionally, by fostering stronger ties between banks and rural communities, our project has the potential to spur economic growth in areas where access to financial resources is limited. Furthermore, as our system evolves and incorporates additional data sources and advanced machine learning techniques, its predictive capabilities are poised to improve, offering even greater value to both applicants and financial institutions. Ultimately, by harnessing the potential of machine learning to improve access to agricultural finance, our project represents a significant stride toward addressing enduring challenges within the agricultural sector.

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