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FinCop: A Smart Digital Platform for Cooperative Societies with AI-Based Trust Scoring

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ABSTRACT:

Cooperative societies provide important financial and community services to farmers, small workers, and rural households. However, paper-based records and disconnected digital systems can make member management, loan processing, grievance handling, and scheme access difficult to monitor. This paper presents FinCop, a proposed cloud-enabled digital platform that integrates cooperative member services with AI-assisted financial assessment.

The platform is designed to support digital registration, member and staff management, loan-application tracking, grievance handling, financial record management, and administrative dashboards. Its central component is a Cooperative Trust Score intended to consider contextual indicators such as income or crop yield, debt-to-income ratio, repayment history, asset ownership, and other relevant member information.

The proposed technical design combines a React and TypeScript frontend, Node.js and Express services, a central data layer, and machine-learning components for repayment-risk prediction and anomaly detection. XGBoost and explainability methods such as SHAP are proposed to support risk assessment and make individual predictions more interpretable, while Isolation Forest is considered for identifying unusual patterns. This paper describes the motivation, related research, system design, methodology, and evaluation plan. Quantitative performance is not claimed because validated experimental results are not provided in the supplied project material.

Keywords: Cooperative societies, digital governance, trust scoring, credit-risk prediction, explainable AI, XGBoost, anomaly detection, rural financial inclusion.

Introduction:

Cooperative societies play a significant role in delivering credit, subsidies, welfare information, and community-based financial services. They often serve people whose financial histories may be incomplete or not fully represented by conventional credit-scoring systems. At the same time, manual documentation and fragmented applications can create delays, duplicate records, inconsistent reporting, and limited visibility for members and administrators. These challenges motivate a unified digital system that supports both day-to-day cooperative operations and more transparent financial decision support.

FinCop is proposed as an integrated platform for cooperative members, society staff, and administrators. It brings member registration, profile management, loan tracking, grievance submission, financial records, and monitoring dashboards into one application. In addition to digitising services, the platform proposes a Cooperative Trust Score to organise relevant financial and behavioural information into an interpretable assessment that can assist, rather than replace, authorised human decision-makers.

The main contributions of the proposed work are:

1. A unified digital-management concept for cooperative societies.
2. A locally contextualised trust-scoring framework using member and financial attributes.
3. Integration of machine-learning-based repayment-risk prediction and anomaly detection.
4. An evaluation plan that considers both predictive performance and the transparency of individual decisions.

Literature Review:

Research on explainable artificial intelligence (XAI) for credit scoring highlights the need to make model-supported loan decisions understandable to applicants and institutions [1]. Interpretability can help reveal which input features influence a prediction, but an explainable model alone does not provide the operational functions needed to manage a cooperative society. FinCop adopts this general direction and proposes to combine explainable risk assessment

with digital member services. Studies of digital finance and rural households examine how digital access affects saving, borrowing, payments, and other financial behaviours [2]. Research on computerisation of Primary Agricultural Cooperative Societies (PACS) has also considered transparency, operational efficiency, and constraints in existing systems [3]. These areas suggest that digital transformation must address usability and process integration, not only the automation of individual transactions.

Machine-learning studies have explored loan-default prediction and micro-credit scoring using models such as XGBoost, Random Forest, AdaBoost, Decision Trees, and Support Vector Machines. Explainability approaches, including SHAP and surrogate models, can help interpret risk predictions [4], [5], [11]. Research focused on farmer and microfinance credit risk is particularly relevant because income and repayment patterns may differ from those of conventional salaried borrowers [12], [13]. These methods provide candidate techniques for FinCop, but their performance must be validated on suitable cooperative data before deployment.

Other related work addresses duplicate-record resolution [7], ICT adoption challenges in PACS [6], digital transformation of cooperative credit societies [8], and AI-based access to government schemes [9]. Together, these studies motivate an integrated design that combines reliable records, accessible digital services, risk analysis, and monitoring. The supplied project materials identify this integration as the central gap addressed by FinCop.

Terminologies used in the proposed framework

Technique	Purpose in Existing Research	Relevance to Proposed Project
Artificial Intelligence (AI)	Automated analysis and decision support	Provides the core intelligence for cooperative member assessment and decision support
Machine Learning (ML)	Predict risk, classify users, and identify patterns	Used to develop the AI-based trust scoring model from financial and behavioural data
Explainable AI (XAI)	Explain the factors influencing AI predictions	Provides transparent explanations for the factors contributing to each member's trust score
Natural Language Processing (NLP)	Understand and process text-based information	Enables processing of member queries, complaints, feedback, and cooperative-related text
Trust Scoring	Assess reliability using financial and behavioural factors	Generates an AI-based trust score for cooperative members using factors such as repayment history, savings, transactions, and participation

Research Gap & Objectives:

Previous studies have examined cooperative society digitalisation, credit-risk prediction, explainable AI, and fraud detection. However, these areas are often addressed as separate problems. For example, some systems focus mainly on maintaining digital records or managing loan applications, while others concentrate on predicting credit risk using financial data. Bringing these functions together in a single platform for cooperative societies remains an important area for further research.

Another limitation is that financial assessment often relies on conventional indicators, such as income, loan history, and repayment records. For cooperative members, additional information, including savings patterns, transaction behaviour, and participation in cooperative activities, may also be relevant when assessing financial reliability. However, the usefulness of these factors needs to be evaluated using appropriate data rather than assumed.

Understanding AI-generated financial assessments is equally important. If a system provides a score without explaining the factors behind it, members and society administrators may find it difficult to understand or review the outcome. Similarly, integrating anomaly detection and decision-support features with everyday cooperative services presents a further challenge.

To address these issues, this study proposes FinCop, a digital platform that combines cooperative society services with AI-assisted financial assessment. The proposed system aims to bring member management, loan tracking, trust scoring, risk analysis, and anomaly detection into a common platform. It also considers explainability as an important part of financial assessment, allowing relevant factors behind a model's prediction to be examined. The effectiveness of these features will need to be established through implementation and experimental evaluation.

FinCop therefore aims to:

1. Centralise cooperative member and service records.
2. Support online registration and loan-application tracking.
3. Generate an AI-assisted Cooperative Trust Score from relevant financial and member information.
4. Explain the factors contributing to risk estimates.
5. Flag possible duplicate or unusual records.
6. Provide dashboards for authorised staff and administrators.

These are system objectives and require evaluation against functional, data-quality, and model-performance criteria.

How the Proposed Project Addresses the Gap

Existing Research Limitation	Proposed Project Solution
Cooperative services handled through separate systems	Unified digital platform for cooperative member and financial management
Dependence on traditional credit assessment	AI-based member trust and risk scoring
Limited use of behavioural information	Integration of financial and behavioural member data
Limited explainability of AI-based decisions	Explainable trust scores with key contributing factors
Limited fraud and anomaly detection	AI-based identification of suspicious or unusual activities
Manual monitoring and decision-making	Automated analysis and intelligent decision support
Limited personalised financial assessment	Member-specific trust and risk assessment
Fragmented member information	Centralised member data and activity management
Limited real-time monitoring	Digital monitoring of transactions and member activities
Limited integration of member feedback	Grievance and feedback management within the platform

A. System Overview

The proposed system has three main user groups: cooperative members or citizens, society staff, and administrators or district officials.

Members can register, maintain profiles, submit loan applications, track application status, and raise grievances. Society staff can review member information and manage operational records. Administrators can view dashboards for monitoring applications, financial activities, and service status.

Access permissions should be defined by role so that sensitive financial and identity data are available only to authorised users.

B. Architecture and Technology

The project presentation identifies React and TypeScript for the frontend and Node.js with Express for backend APIs. The proposed data layer includes MongoDB Atlas, while the technology-stack slide also lists PostgreSQL. The final implementation should select and document the authoritative database configuration rather than implying that both are necessarily used for the same records.

Python, Pandas, NumPy, and scikit-learn are proposed for data preparation and model workflows. XGBoost and Gradient Boosting are candidate predictive models, Isolation Forest is proposed for anomaly detection, and SHAP is proposed for explaining model outputs. JWT-based authentication and bcrypt password hashing are identified as security components.

C. Cooperative Trust Score

The Cooperative Trust Score is intended to summarise information relevant to a member's financial reliability in a way that is more contextual than a conventional credit score.

Candidate features listed in the project material include:

- Income or crop yield.
- Debt-to-income ratio.
- Repayment history.
- Asset ownership.
- Peer validation.

Additional transaction, savings, or participation variables should only be included when they are lawfully collected, sufficiently reliable, and justified for the intended purpose.

The score should be accompanied by an explanation of the main contributing factors and should not be treated as an automatic final loan decision.

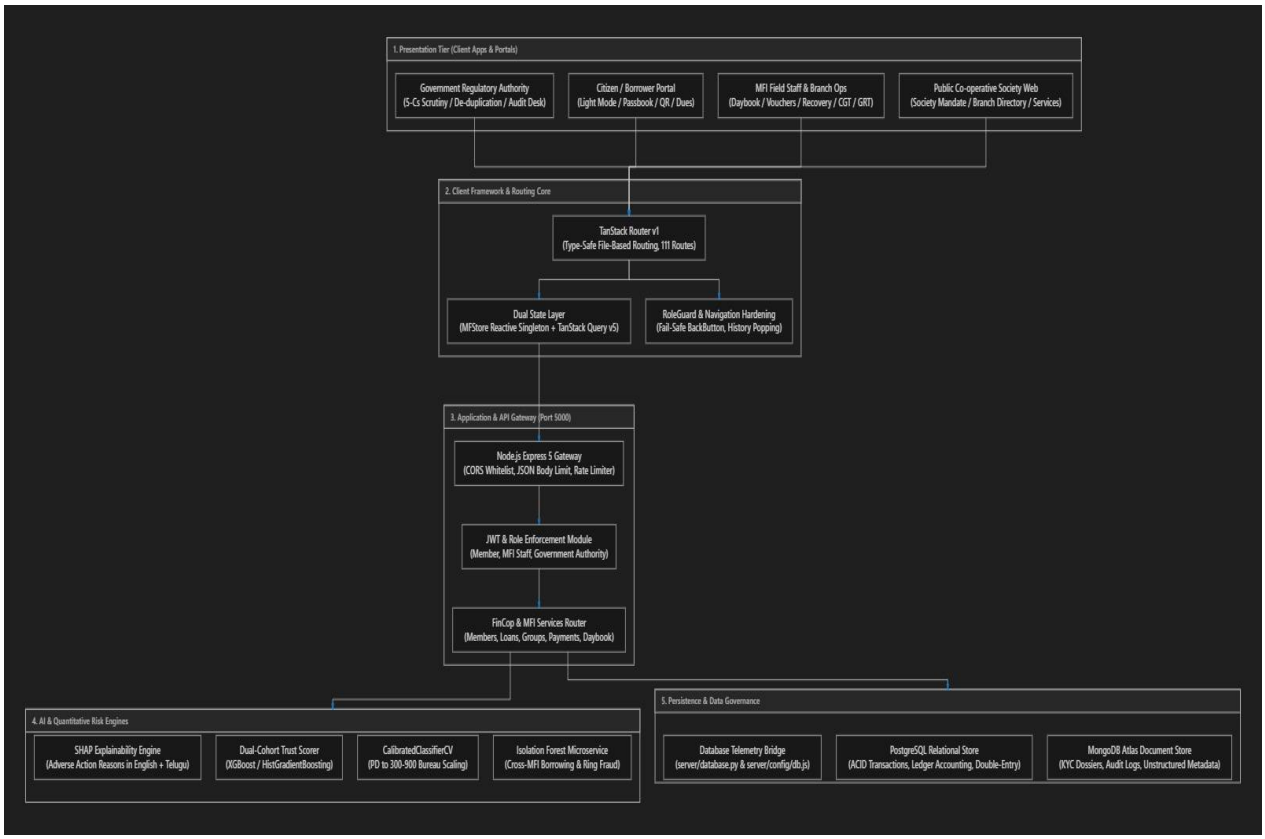
D. Duplicate and Anomaly Detection

Duplicate-member detection can compare identity and profile fields to identify potentially repeated records for staff review. Isolation Forest is proposed to flag unusual financial patterns or transactions.

Such flags are indicators for further examination, not proof of fraud. False positives, data-entry errors, and legitimate exceptional activity must be

considered during review.

Methodology:



A. Data Collection and Preparation

The supplied presentation describes cooperative member and loan records containing attributes such as income, loan amount, loan term, repayment history, outstanding balances, collection data, property or asset information, and loan status.

Before modelling, the project should document the origin, permissions, time period, data dictionary, and quality of each dataset. Personally identifiable information should be minimised or removed from model-development copies wherever possible. Missing values, inconsistent categories, duplicate entries, and outliers should be assessed before training.

B. Feature Engineering and Data Splitting

Candidate features can include debt-to-income ratio, repayment behaviour, overdue amount, income stability, and asset indicators where supported by available data.

Feature definitions must be consistent and calculated without using information that would not have been available at the time of the prediction. The dataset should be divided into training, validation, and test subsets. If records span time, a time-aware split is preferable to reduce leakage from future repayment outcomes into earlier predictions.

Class imbalance should be measured before deciding whether a method such as class weighting or resampling is appropriate.

C. Model Training and Explainability

XGBoost and Gradient Boosting are proposed for repayment-risk prediction, with simpler baselines such as logistic regression or a decision tree included for comparison where feasible.

Hyperparameters should be selected using training and validation data, and final performance should be reported only on held-out test data. SHAP values may be used to describe global feature importance and the factors contributing to individual predictions. Explanations should be checked for stability and should not be presented as causal evidence.

D. Trust Score and Decision Support

The predictive risk output can be mapped to a clearly documented score or risk band only after the score definition, calibration, direction, and thresholds are established. A trust score should not be assigned arbitrary weights without validation.

Where a rule-based component is used, its rules and rationale should be disclosed. The interface should show the score alongside its key factors, relevant data limitations, and a route for authorised staff to review or correct inaccurate information.

E. Evaluation Plan

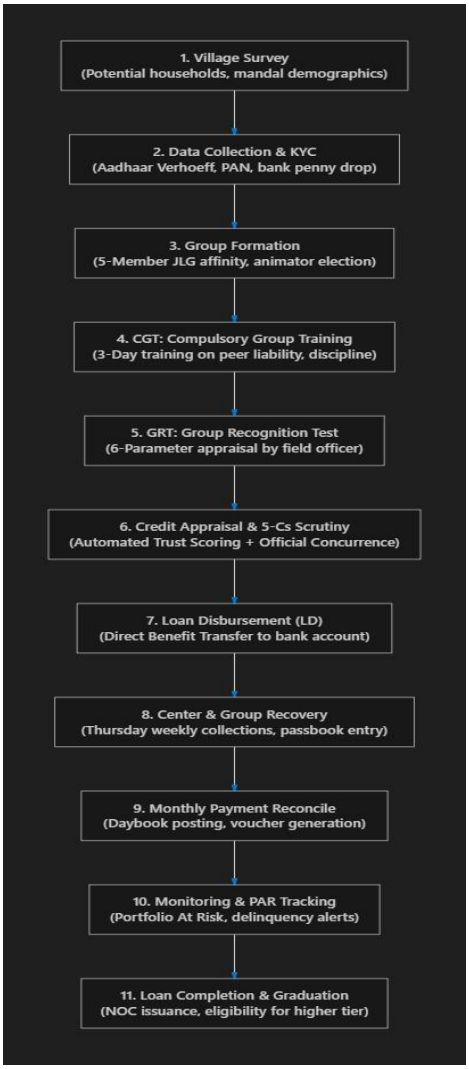
Classification performance should be measured using precision, recall, F1-score, and ROC-AUC, with accuracy reported where class distribution makes it informative. Confusion matrices and class-wise results should also be included.

SHAP-based explanations can be assessed for consistency and usefulness. If a surrogate model is used, its agreement with the original model may be measured. Anomaly detection should be evaluated using labelled cases if available and through a documented human-review process otherwise.

Platform testing should cover:

- Role-based access and authentication.
- Member registration and profile management.
- Loan tracking and status updates.
- Grievance handling.
- Data validation and duplicate-record checks.
- Response time and usability.

No numerical result is reported in this draft because validated experiment outputs were not included in the supplied material.



System Implementation:

The FinCop platform is organised into six major components: frontend, backend, database, data processing, machine learning, and AI technologies. These components work together to manage cooperative society operations and support AI-assisted financial assessment.

6.1 Frontend Implementation

The frontend is developed using React and TypeScript, with Tailwind CSS for styling. TanStack Router is used for navigation, while React Hook Form supports form handling and user input validation. The interface is intended to provide access to member registration, loan applications, grievance management, and administrative dashboards.

6.2 Backend Implementation

The backend uses Node.js and Express.js to provide REST APIs for communication between the frontend, database, and processing components. JWT authentication supports user authentication, while bcryptjs is used for password hashing. These components are intended to support secure access and role-based operations.

6.3 Database Implementation

PostgreSQL and MongoDB Atlas are included in the proposed database stack. SQLAlchemy and Mongoose are listed for database connectivity and data operations. The database layer is intended to manage member profiles, financial records, loan applications, repayment information, and related cooperative data. The final implementation should clarify which database stores each category of information.

6.4 Data Processing and Preprocessing

Python is used for data-processing tasks, with Pandas and NumPy supporting data manipulation and numerical operations. Feature engineering is used to derive relevant financial attributes, while data validation and preprocessing address missing values, inconsistent records, and data-quality issues before model training.

6.5 Machine-Learning Implementation

The machine-learning component includes Scikit-learn, XGBoost, Gradient Boosting, CalibratedClassifierCV, and Isolation Forest. These techniques serve different purposes:

- XGBoost and Gradient Boosting: candidate models for predicting financial risk.
- CalibratedClassifierCV: calibration of model probability estimates.
- Isolation Forest: identification of unusual data patterns.
- Scikit-learn: preprocessing, model development, and evaluation.

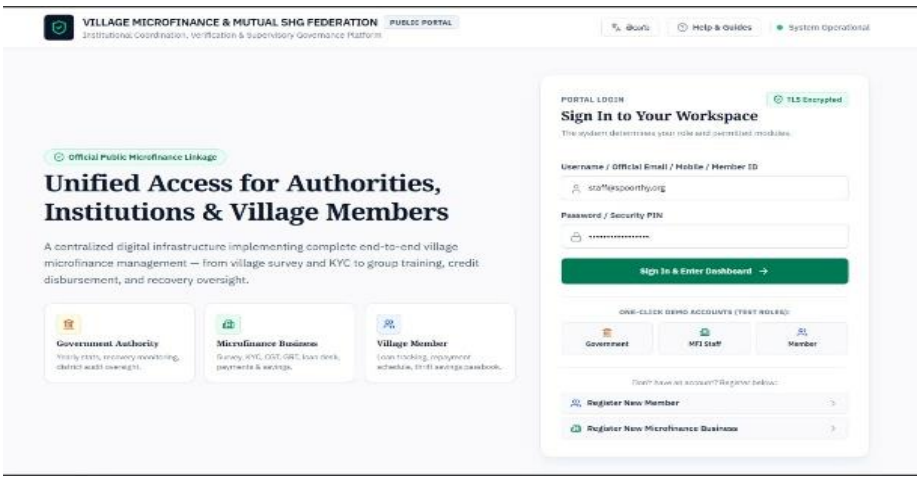
The models should be compared using suitable evaluation metrics before selecting a final approach.

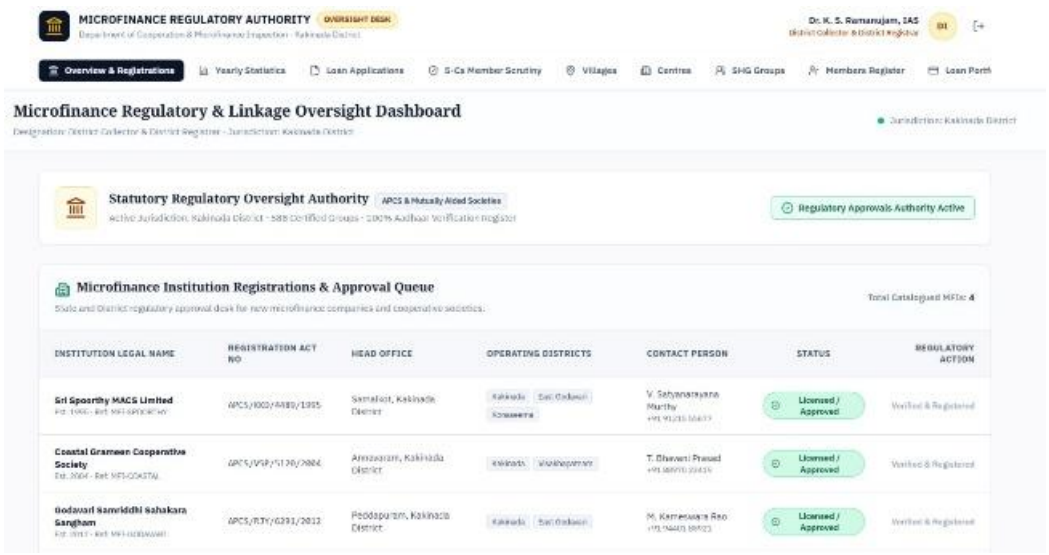
6.6 AI Technologies and Trust Assessment

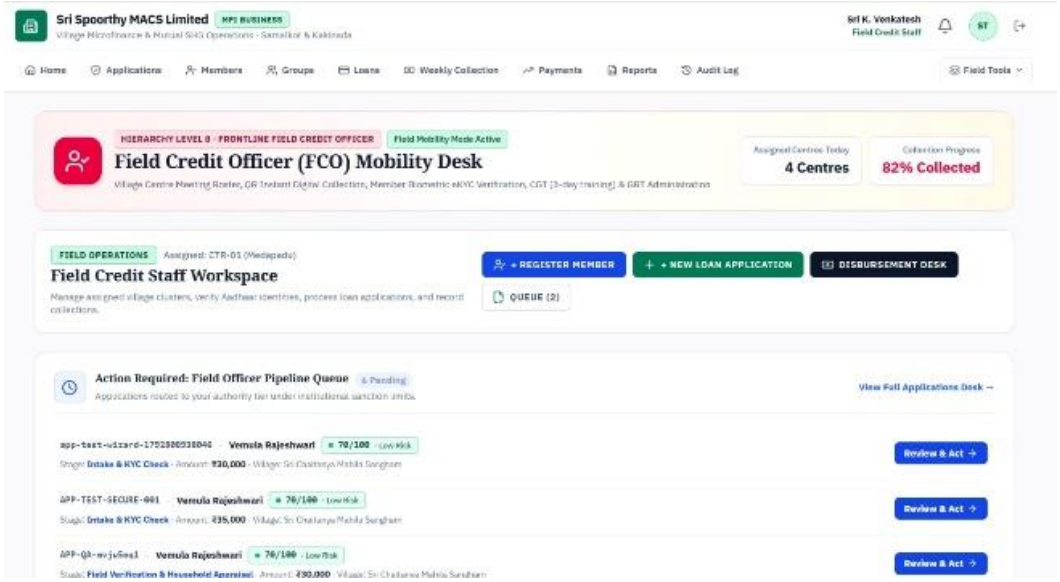
The AI component includes SHAP for explainable AI, a retrieval-augmented generation (RAG) approach for credit assessment, an Indic-BERT/Transformer pipeline, a Cooperative Trust Score, and predictive analytics.

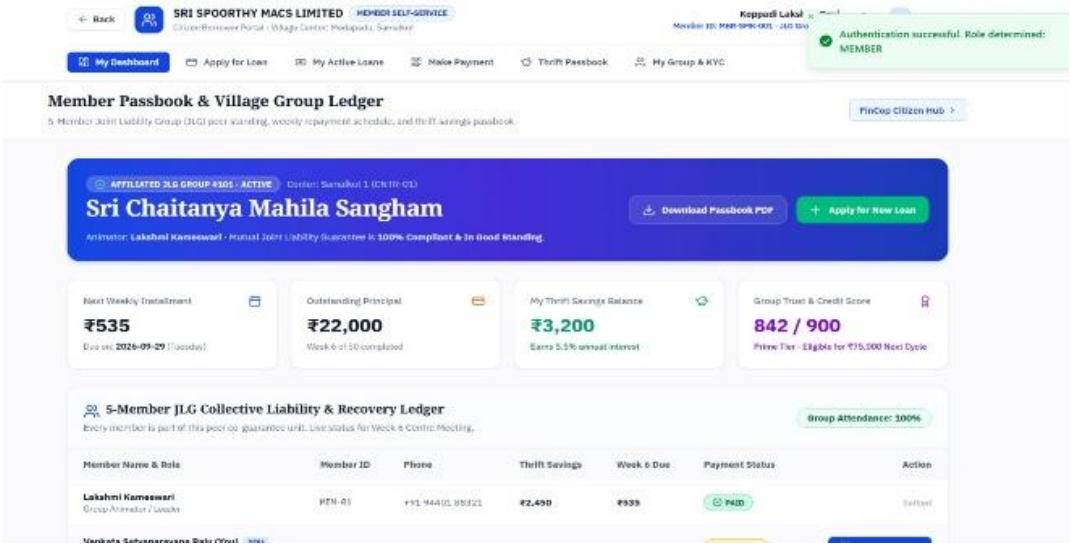
SHAP is intended to explain the contribution of input features to model predictions. The RAG-based component may support information retrieval and contextual responses, while the Indic-BERT/Transformer pipeline may support language-related tasks if those functions are implemented. The Cooperative Trust Score is intended to combine relevant member and financial indicators into an interpretable assessment.

These components should be integrated according to their specific purposes, with AI-generated recommendations treated as decision-support information rather than automatic loan decisions.




MICROFINANCE REGULATORY AUTHORITY
Microfinance Regulatory & Linkage Oversight Dashboard
Statutory Regulatory Oversight Authority
Microfinance Institution Registrations & Approval Queue


Sri Spoorthy MACS Limited
Field Credit Officer (FCO) Mobility Desk
Field Credit Staff Workspace
Action Required: Field Officer Pipeline Queue


SRI SPOORTHY MACS LIMITED
Member Passbook & Village Group Ledger
Sri Chaitanya Mahila Sangham
5-Member JLG Collective Liability & Recovery Ledger

Feature Scaling and Preprocessing

Feature scaling is part of the data-processing stage in FinCop. Financial datasets may contain attributes with different units, such as income, loan amounts, repayment counts, and debt-to-income ratios. Scaling can help algorithms that are sensitive to differences in feature magnitude.

Min-Max scaling transforms a numerical value into a range, typically 0 to 1:

\[x'=\frac{x-x_{\min}}{x_{\max}-x_{\min}} \]

Standardisation transforms values using the mean and standard deviation:

\[z=\frac{x-\mu}{\sigma} \]

The appropriate method depends on the selected model. Scaling is generally useful for algorithms such as Support Vector Machines and logistic regression, but is usually not required for tree-based models such as XGBoost.

For reliable evaluation, the scaler should be fitted using the training data only and then applied to the validation and test data. Missing-value handling, duplicate checks, data validation, and feature engineering should also be performed as part of the preprocessing workflow.

Discussion

FinCop's intended value lies in connecting operational digitisation with interpretable financial decision support. A shared platform can reduce duplicated data entry and improve the visibility of application status, while a trust-scoring component may help organise relevant information for human review.

However, these benefits depend on data completeness, model validation, secure implementation, user accessibility, and governance. In rural settings, incomplete records and varying income patterns may affect model reliability. A model trained on one cooperative or region may not generalise to another without further testing.

Fairness and accountability are essential because loan-related recommendations can influence access to financial services. Sensitive attributes should not be used casually, and proxy variables may still create unintended disparities. The system should preserve an auditable record of inputs, model versions, explanations, and human decisions, while providing correction and appeal mechanisms.

AI outputs should remain decision-support signals rather than unquestioned approval or rejection rules.

Conclusion

This paper presented FinCop, a proposed digital platform for cooperative society management with AI-assisted trust scoring. The design integrates member registration, loan tracking, grievance handling, financial records, administrative dashboards, repayment-risk prediction, explainability, and anomaly detection.

By combining digital services with interpretable assessment, FinCop aims to support more transparent and consistent cooperative operations. Its practical effectiveness remains to be established through implementation, data validation, model evaluation, security testing, and user studies. These steps are necessary before making claims about predictive accuracy or operational impact.

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