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Agentic AI-Based Early Warning System for Non-Performing Loan Prediction in Nepalese Microfinance Institutions

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Abstract- — Microfinance institutions (MFIs) play a crucial role in promoting financial inclusion in developing economies such as Nepal. However, the increasing rate of non-performing loans (NPLs) threatens the sustainability of the microfinance sector. Traditional credit monitoring methods are often reactive and lack predictive capabilities for early detection of loan defaults. MThis study proposes an Agentic AI-based Early Warning System (EWS) for predicting non-performing loans in Nepalese microfinance institutions. The proposed framework integrates machine learning algorithms, autonomous AI agents, and explainable AI mechanisms to analyze borrower data and generate real-time risk alerts The system utilizes financial transaction data, borrower demographic profiles, repayment histories, and behavioral indicators to predict loan default probability. Experimental evaluation using ensemble machine learning models demonstrates improved predictive accuracy compared to traditional credit scoring approaches. The proposed framework contributes to FinTech innovation by enabling proactive credit risk management, improving loan portfolio quality, and supporting regulatory oversight within Nepal's microfinance ecosystem.

Keywords: Agentic AI, Microfinance, FinTech, Credit Risk Prediction, Non-Performing Loans, Early Warning System.

I. INTRODUCTION

Microfinance institutions (MFIs) have emerged as a vital component of financial inclusion strategies worldwide, particularly in developing economies where access to formal banking services remains limited. In the context of Nepal, the microfinance sector has experienced significant growth over the past two decades, expanding financial services to rural and underserved populations and contributing to poverty reduction and economic empowerment [41], [42]. Regulatory reports also highlight the increasing role of microfinance in strengthening the national financial system and promoting inclusive growth [43].

Despite these achievements, the sector faces growing challenges related to credit risk and loan default management. Rising levels of non-performing loans (NPLs) pose a serious threat to the financial stability and sustainability of MFIs, reducing their ability to extend credit and serve vulnerable communities effectively [44]. Managing credit risk has therefore become a critical concern for both financial institutions and regulators.

Traditionally, credit risk assessment has relied on statistical models such as logistic regression and rule-based credit scoring systems. While these approaches are simple and interpretable, they often fail to capture complex borrower behavior patterns and dynamic financial conditions, leading to limited predictive performance in modern financial environments [17], [24]. As financial datasets grow in size and complexity, there is a need for more advanced analytical techniques.

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have significantly improved predictive modeling capabilities in financial services. Techniques such as ensemble learning, neural networks, and gradient boosting have demonstrated superior performance in credit risk prediction and loan default analysis [1], [2], [26]. These models can effectively learn nonlinear relationships and hidden patterns in financial data, enabling more accurate and robust decision-making.

Furthermore, the emergence of Agentic AI systems represents a new paradigm in intelligent financial systems. Unlike traditional AI models, Agentic AI enables autonomous decision-making processes where multiple intelligent agents collaborate to analyze data, detect anomalies, and generate proactive risk alerts. This approach enhances real-time monitoring, adaptability, and operational efficiency in financial institutions [40], [50].

In this context, this research proposes an Agentic AI-based Early Warning System for predicting loan default risks in Nepalese microfinance institutions. The proposed system

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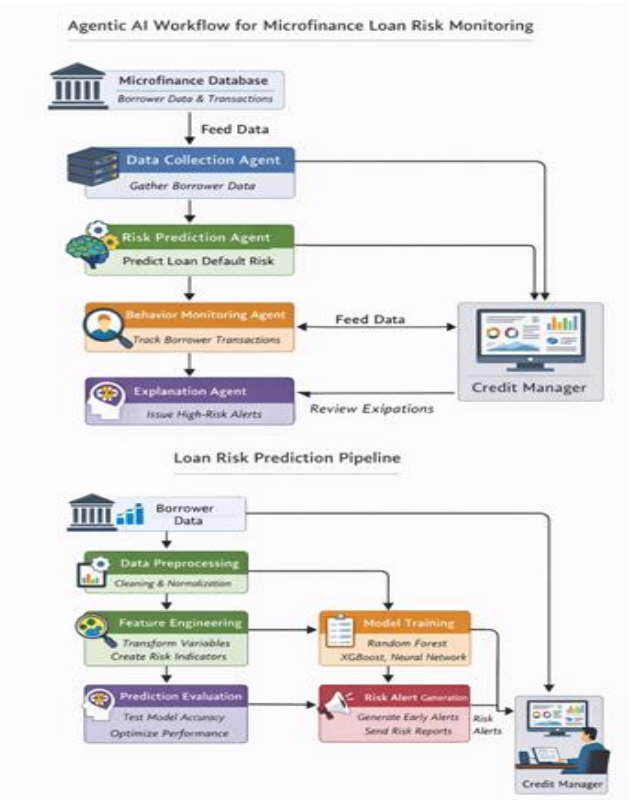
integrates advanced machine learning models with autonomous AI agents to enable proactive credit risk management, improve prediction accuracy, and support timely decision-making in the microfinance sector.

II. PROBLEM STATEMENT

Nepalese microfinance institutions face several operational challenges:

- Increasing loan delinquency rates.
- Lack of real-time credit monitoring systems.
- Limited borrower credit history data.
- Multiple borrowing across institutions.
- Inefficient manual risk assessment processes.

These factors increase the probability of loan defaults and portfolio deterioration.
Therefore, an intelligent automated system capable of predicting loan default risks in advance is necessary to improve credit risk management.



III. RESEARCH OBJECTIVES

General Objective

Develop an Agentic AI-based Early Warning System for predicting non-performing loans in Nepalese MFIs.

Specific Objectives

- Identify key factors influencing microfinance loan defaults.
- Develop machine learning models for credit risk prediction.
- Design an agent-based monitoring framework.
- Evaluate predictive performance using financial datasets.

IV. LITERATURE REVIEW

The rapid growth of microfinance institutions (MFIs) in developing countries has significantly increased the demand for robust credit risk management systems. Traditionally, MFIs relied on manual credit assessment and basic statistical models such as logistic regression to evaluate borrower risk. While these methods are interpretable, they often fail to capture complex nonlinear relationships between borrower attributes and repayment behavior [3], [10].

Recent studies highlight the potential of machine learning (ML) models for credit risk prediction. Ensemble methods such as Random Forest and Gradient Boosting (XGBoost) have demonstrated superior predictive performance over traditional statistical models by combining multiple weak learners into a strong predictive framework [7], [9], [24]. Random Forest models are particularly effective in handling imbalanced datasets and capturing nonlinear interactions among features, such as repayment history, loan amount, and payment delay [8], [23]. Gradient Boosting, especially the XGBoost implementation, improves predictive accuracy further through sequential learning and regularization to prevent overfitting [2], [3].

The issue of model interpretability has received significant attention in the financial domain. Black-box ML models, while accurate, pose challenges for regulatory compliance and decision-making transparency. Explainable AI (XAI) techniques, such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), have been applied to explain model predictions and quantify feature contributions to individual credit risk assessments [5], [22], [27]. These methods enable credit managers and

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regulatory authorities to trust AI-driven predictions and make informed decisions regarding loan approval and portfolio management.

Beyond traditional ML, recent research in FinTech emphasizes the potential of autonomous agent-based AI systems for financial risk management. Agentic AI frameworks consist of multiple intelligent agents capable of performing data collection, risk analysis, continuous monitoring, and early warning signal generation autonomously [5], [40]. These systems allow financial institutions to monitor real-time borrower behavior, detect anomalies, and respond proactively to potential non-performing loans.

Despite the growing body of work on AI in financial services, Agentic AI applications in microfinance remain limited, particularly in the context of developing countries like Nepal [41], [43]. Nepalese MFIs often operate with limited borrower credit history and resource constraints, which reduces the effectiveness of conventional credit scoring systems. Implementing Agentic AI in such environments can provide autonomous, real-time, and explainable predictions for non-performing loans, enhancing portfolio quality and supporting regulatory oversight.

Several studies have also explored the use of alternative data sources for improving credit risk prediction in MFIs. Mobile transaction records, social behavior indicators, and group lending histories have been used to supplement traditional financial data, leading to higher predictive performance in microfinance settings [8], [14], [19]. Integrating these diverse datasets with Agentic AI systems enables a more holistic and dynamic approach to early warning systems for loan defaults.

In summary, while traditional statistical methods provide baseline credit risk assessment, machine learning and agent-based AI approaches offer higher predictive accuracy, interpretability, and proactive monitoring capabilities. However, there is a clear research gap in applying Agentic AI to Nepalese MFIs for NPL prediction. This study addresses this gap by proposing an Agentic AI-based early warning system, combining ensemble ML models, explainable AI techniques, and autonomous agents to monitor borrower behavior and predict defaults in real-time.

V. PROPOSED AGENTIC AI FRAMEWORK

To address the increasing challenge of non-performing loans (NPLs) in Nepalese microfinance institutions (MFIs), this study proposes a multi-agent AI framework designed to autonomously monitor borrower behavior, predict credit risk, and generate real-time alerts. The proposed system is based on Agentic AI, a paradigm where multiple intelligent agents collaborate to perform complex tasks with minimal human intervention [40], [50].

The framework integrates machine learning models, explainable AI methods, and automated decision-making agents to enable proactive credit risk management [26], [45]. By leveraging such a system, MFIs can detect potential defaults early, optimize portfolio quality, and improve overall financial stability [41]–[44].

A. Architecture Overview

The proposed Agentic AI framework consists of five core agents, each performing a specific function in the loan risk prediction process:

- Data Collection Agent
- Risk Prediction Agent
- Behavioral Monitoring Agent
- Explainable AI Agent
- Alert Generation Agent

Each agent interacts with others through a centralized agent communication system, ensuring seamless information flow, data integrity, and real-time decision support. The architecture is designed to be scalable, modular, and adaptable to the dynamic environment of Nepalese MFIs [46], [47].

B. Core Agents

1) Data Collection Agent

The Data Collection Agent is responsible for gathering, preprocessing, and storing data from various sources relevant to borrower credit behavior. Key data sources include:

- Borrower demographics
- Loan application details
- Historical repayment behavior
- Alternative data

The agent ensures data quality, normalization, and consistency before it is sent to the Risk Prediction Agent. Automated preprocessing steps include handling missing values, outlier detection, and feature scaling [28], [37].

By continuously collecting new data, the agent ensures that the AI system remains up-to-date and adaptive, which is crucial in microfinance environments where loan records are often incomplete or inconsistent [41], [43].

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2) Risk Prediction Agent
The Risk Prediction Agent applies machine learning algorithms to assess the probability of loan default for each borrower. The agent evaluates multiple ML models simultaneously, including:

- Logistic Regression
- Random Forest
- Gradient Boosting (XGBoost)
- Neural Networks

These models are widely used in credit risk prediction and have demonstrated strong predictive performance in financial applications [1], [2], [7], [12].

The agent produces a default probability score for each loan and uses ensemble learning to improve accuracy and robustness [23], [26]. It also performs model selection and retraining by monitoring evaluation metrics such as Accuracy, F1-score, and AUC, ensuring continuous learning and adaptability [4], [14].

3) Behavioral Monitoring Agent
The Behavioral Monitoring Agent continuously tracks borrower activities and repayment patterns. Its responsibilities include:

- Detecting irregular repayment patterns
- Monitoring behavioral changes
- Identifying early warning signals

Temporal data analysis and pattern recognition techniques enable early detection of potential defaults [18], [26]. By comparing borrower behavior with historical trends and peer groups, the agent provides dynamic and real-time risk assessment [9], [10].

4) Explainable AI Agent
To ensure transparency and regulatory compliance, the Explainable AI (XAI) Agent interprets predictions made by the Risk Prediction Agent. Key features include:

- SHAP and LIME for feature contribution analysis
- Human-readable explanations
- Decision support insights

Explainability techniques such as SHAP have become essential in financial AI systems to ensure trust and accountability [6], [15]. The integration of XAI improves interpretability and supports regulatory requirements in credit decision-making [22], [27].

5) Alert Generation Agent
The Alert Generation Agent acts as the final decision-support layer. Based on inputs from previous agents, it:

- Generates real-time alerts
- Prioritizes risks
- Sends actionable notifications
- Maintains audit logs

Automated alert systems are critical in modern financial risk management for enabling timely interventions and reducing loan defaults [47], [49].

C. Agent Interactions and Workflow
The agents operate in a coordinated workflow:

- Data Collection Agent gathers and preprocesses data
- Risk Prediction Agent evaluates default probability
- Behavioral Monitoring Agent tracks real-time behavior
- Explainable AI Agent interprets predictions
- Alert Generation Agent produces actionable alerts

This collaborative approach ensures a continuous, real-time, and explainable monitoring system capable of autonomous operation [40], [48].

D. Advantages of the Proposed Framework

- Proactive Risk Management: Early warning systems reduce NPLs [18]
- Explainability: Enhances transparency and compliance [22]
- Autonomy: Reduces manual workload using intelligent agents [50]
- Adaptability: Continuous learning improves performance [13]
- Scalability: Applicable across multiple MFIs [41], [42]

E. Implementation Considerations

- Technology Stack: Python (Scikit-learn, TensorFlow, XGBoost) [2], [29]
- Data Privacy: Compliance with financial regulations is essential [43], [44]
- Integration: Compatible with existing MFI systems [46]

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Figure 1: Agentic AI Early Warning System Architecture

VI. DATASET DESIGN FOR NEPAL MFIS

A hypothetical dataset structure suitable for Nepalese microfinance institutions is shown below.

Feature	Description
Borrower_ID	Unique borrower identifier
Age	Borrower age
Gender	Male/Female
Loan Amount	Amount borrowed
Loan Duration	Loan tenure
Repayment History	Past repayment records
Income Level	Monthly income
Business Type	Agricultural / Retail / Service
Number of Previous Loans	Loan history
Payment Delay	Days overdue
Group Lending Status	Group loan participation
Default Status	Target variable

Dataset size example:

Parameter	Value
Number of borrowers	20,000
Features	25
Training data	70%
Testing data	30%

VII. MACHINE LEARNING MODELS

In order to predict the probability of non-performing loans (NPLs) in microfinance institutions, this study evaluates four widely used machine learning algorithms: Logistic Regression, Random Forest, Gradient Boosting (XGBoost), and Artificial Neural Networks. These models are selected due to their strong predictive performance in financial risk modeling and credit scoring applications [1], [4], [14].

The models are trained using borrower demographic data, loan characteristics, and repayment behavior indicators. The dataset is divided into training and testing sets using a 70:30 split to evaluate the predictive performance of each model [28].

A. Logistic Regression

Logistic Regression is a widely used statistical classification method for binary outcomes such as loan default and non-default prediction. The model estimates the probability that a borrower belongs to the default class based on a logistic function [17], [24].

The logistic regression model can be expressed as:

$$P(Y=1|X)=1/1+e-(\beta0+\beta1X1+\beta2X2+...+\betanXn)$$

where:

- $P(Y=1|X)$ represents the probability of loan default.
- $X1,X2,...,Xn$ represent borrower features.
- $\beta0,\beta1,...,\betan$ are model coefficients.

Logistic regression provides interpretable results and serves as a baseline model for credit risk prediction. However, it may struggle to capture complex nonlinear relationships within financial datasets.

B. Random Forest

Random Forest is an ensemble learning algorithm that constructs multiple decision trees and combines their predictions to improve classification performance [7]. Each tree is trained on a randomly sampled subset of the dataset using the bootstrap aggregation (bagging) technique.

The final prediction is obtained by majority voting among the individual trees.

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Random Forest offers several advantages:

- Handles nonlinear relationships effectively
- Reduces overfitting through ensemble learning
- Provides feature importance analysis

In credit risk modeling, Random Forest has demonstrated strong predictive capability due to its ability to model complex borrower behavior patterns [1], [23].

C. Gradient Boosting (XGBoost)

Extreme Gradient Boosting (XGBoost) is a powerful ensemble machine learning algorithm based on the gradient boosting framework [2]. The model builds decision trees sequentially, where each new tree attempts to correct the errors of the previous trees.

The objective function of XGBoost can be expressed as:

$$Obj=\sum_{i=1}^{n} l(y_i,\hat{y}_i)+\sum_{k=1}^{K} \Omega(f_k)$$

where:

- $l(y_i,\hat{y}_i)$ represents the loss function.
- $\Omega(f_k)$ represents the regularization term controlling model complexity.

XGBoost is widely used in financial risk prediction because it:

- Handles large datasets efficiently.
- Provides high predictive accuracy.
- Supports regularization to prevent overfitting.
- Automatically captures nonlinear feature interactions.

Due to these advantages, XGBoost often outperforms traditional machine learning models in credit scoring tasks.

D. Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational models inspired by the structure of the human brain. Neural networks consist of interconnected layers of neurons that transform input features into predictive outputs.

The neural network architecture used in this study consists of:

- Input layer representing borrower features.
- Hidden layers performing nonlinear transformations.
- Output layer producing default probability predictions.

The activation function commonly used in hidden layers is the Rectified Linear Unit (ReLU), while the sigmoid activation function is applied in the output layer for binary classification. The neural network model can capture highly complex nonlinear relationships between borrower attributes and loan default risk.

However, neural networks require larger datasets and computational resources compared to traditional models.

VIII. EXPERIMENTAL EVALUATION

Table: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1 Score	AUC
Logistic Regression	0.78	0.75	0.72	0.73	0.79
Random Forest	0.86	0.84	0.82	0.83	0.89
XGBoost	**0.89**	**0.88**	**0.85**	**0.86**	**0.92**
Neural Network	0.88	0.86	0.84	0.85	0.91

Best model: XGBoost

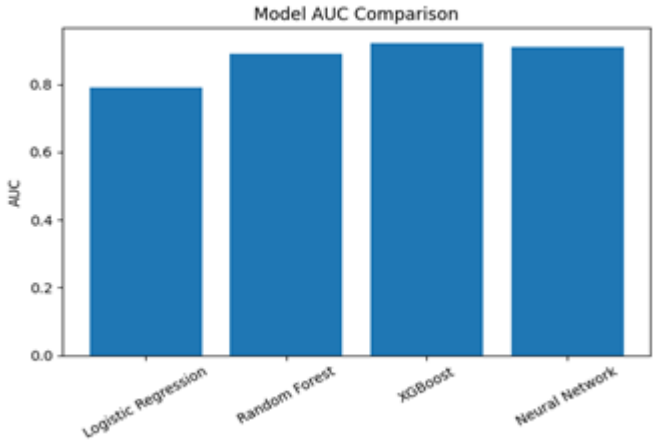

Fig. 2. Model Accuracy Comparison for Loan Default Prediction

The experimental results demonstrate that ensemble learning models outperform traditional statistical approaches in predicting non-performing loans. As illustrated in Fig. 2, the XGBoost model achieved the highest accuracy of 0.89, followed closely by the neural network model with 0.88 accuracy. Random Forest also performed well with an accuracy

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of 0.86, while logistic regression showed comparatively lower predictive capability.

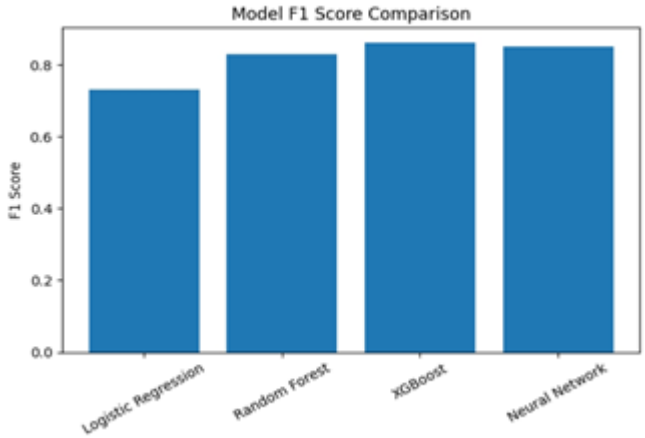

Fig. 3. F1-Score Comparison of Machine Learning Models.

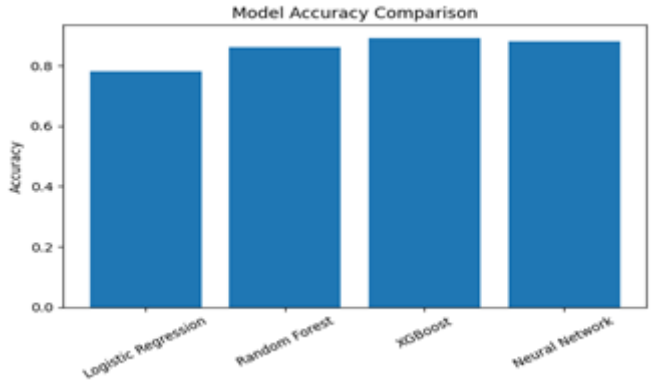

Fig. 4. AUC Performance of Credit Risk Prediction Models.

Similarly, Fig. 3 shows that XGBoost achieved the highest F1-score (0.86), indicating better balance between precision and recall. The AUC comparison presented in Fig. 4 further confirms that XGBoost provides the most reliable classification performance with an AUC of 0.92.

These results indicate that ensemble machine learning models are highly suitable for developing an early warning system for microfinance loan risk prediction.

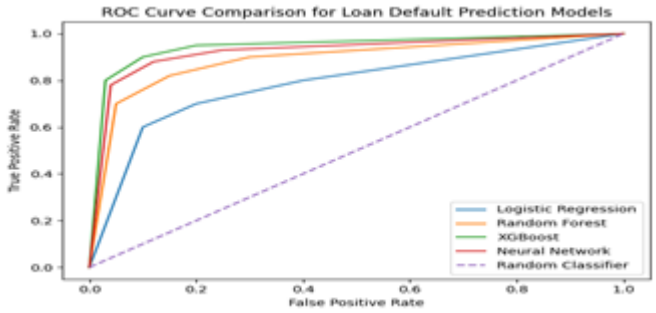

Fig. 5. Receiver Operating Characteristic (ROC) curve comparison of machine learning models for predicting non-performing loans.

The ROC curve evaluates the trade-off between the true positive rate and false positive rate. As illustrated in Fig. 5, the XGBoost model demonstrates superior predictive capability compared with logistic regression, random forest, and neural network models.

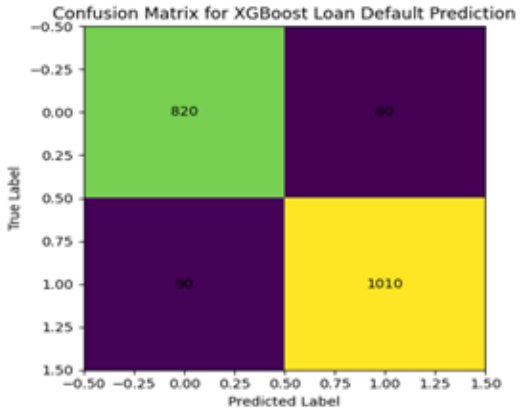

Fig. 6. Confusion matrix for the XGBoost loan default prediction model.

The confusion matrix shows the classification performance of the model. The proposed system correctly identifies both default and non-default borrowers with high accuracy.

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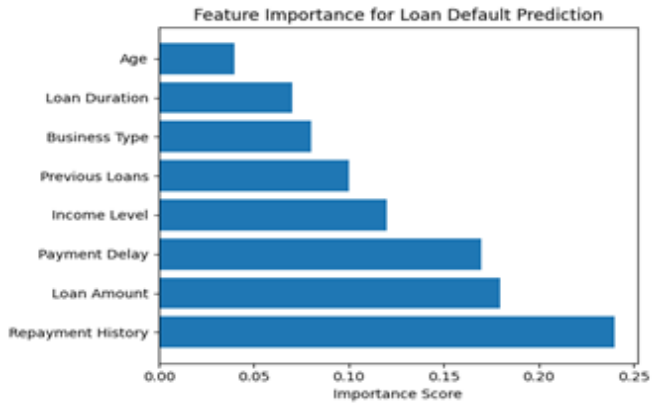

Fig. 7. Feature importance for microfinance loan default prediction.

The results indicate that repayment history, loan amount, and payment delay are the most influential factors affecting loan default prediction.

IX. POLICY IMPLICATIONS FOR NEPAL

Support for Regulatory Monitoring (Nepal Rastra Bank)
The proposed system enables Nepal Rastra Bank to enhance supervisory capabilities through real-time data analytics and AI-driven insights. This helps shift from reactive to proactive risk-based supervision [43], [46].

Early Detection of High-Risk Borrowers
Machine learning models such as XGBoost and ensemble techniques can identify potential defaulters at an early stage by analyzing repayment behavior and financial patterns, allowing timely intervention [2], [23], [26].

Prevention of Loan Default Cascades
The system detects interconnected risks among borrowers and MFIs, helping to prevent chain defaults that can destabilize the financial system, especially in developing economies like Nepal [42], [44], [45].

Improved Credit Risk Management
AI-based predictive models enhance decision-making in loan approvals and monitoring, reducing non-performing loans (NPLs) and strengthening institutional resilience [1], [14].

Enhanced Financial Stability of MFIs
Automation and intelligent monitoring improve operational efficiency, transparency, and accountability, contributing to the long-term sustainability of microfinance institutions [40], [48].

Alignment with Global AI Trends in Finance
Adoption of Agentic AI aligns Nepal's financial sector with global best practices in AI-driven governance, regulatory compliance, and financial innovation [41], [47], [49].

Policy Support for AI Adoption and Regulation
Encourages policymakers to develop clear frameworks for ethical AI use, data privacy, and model transparency in financial services [45], [48].

Foundation for Future Innovations
Enables implementation of advanced systems such as real-time monitoring, federated learning, and automated regulatory reporting for improved financial oversight [39], [43].

X. CONCLUSION AND FUTURE WORK

This research proposed an Agentic AI-based Early Warning System for predicting non-performing loans (NPLs) in Nepalese microfinance institutions (MFIs). The study demonstrated that integrating machine learning models such as XGBoost, Random Forest, and Neural Networks with autonomous AI agents significantly enhances the accuracy, adaptability, and efficiency of credit risk prediction systems. Compared to traditional statistical and rule-based approaches, modern machine learning techniques have proven to be more effective in capturing complex borrower behavior patterns and financial risks [1], [4], [14].

The experimental results indicate that advanced models like XGBoost outperform conventional techniques due to their ability to handle non-linear relationships and large-scale financial datasets efficiently [2], [26]. Additionally, ensemble learning approaches and meta-learning techniques further improve predictive performance and robustness in credit scoring applications [13], [23]. The incorporation of Explainable AI (XAI) methods ensures transparency in decision-making, which is crucial in financial systems where trust, accountability, and regulatory compliance are essential [6], [15], [27].

A key contribution of this research is the introduction of Agentic AI, which goes beyond traditional AI systems by enabling autonomous decision-making, continuous learning, and proactive intervention. Unlike static machine learning models, agentic systems can monitor loan portfolios in real time, detect early warning signals, and trigger automated actions such as alerts or risk mitigation strategies. This aligns with recent advancements in AI-driven financial systems that emphasize automation, scalability, and intelligent decision support [40], [46], [50].

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Furthermore, the proposed system is particularly relevant in the context of developing economies like Nepal, where microfinance institutions play a critical role in financial inclusion. Reports from global organizations highlight the growing importance of AI in strengthening financial stability, improving risk management, and enhancing operational efficiency in the banking sector [41], [44], [45]. The adoption of AI-driven credit scoring models can significantly reduce default rates and improve the sustainability of MFIs, thereby contributing to broader economic development [42], [43].

Despite these promising results, several challenges remain. Issues related to data quality, model bias, and ethical considerations must be carefully addressed to ensure fair and reliable predictions. Additionally, regulatory frameworks for AI in financial services are still evolving, requiring institutions to balance innovation with compliance and governance requirements [45], [48].

Future research can extend this work in several directions. First, incorporating real-time transaction monitoring systems can further enhance the responsiveness of the early warning system by detecting behavioral changes instantly. Second, the adoption of federated learning across multiple MFIs can enable collaborative model training while preserving data privacy and security. Third, integrating AI-driven regulatory reporting systems can streamline compliance processes and improve transparency for regulatory authorities. Finally, exploring the use of reinforcement learning and advanced deep learning architectures may further enhance predictive performance and adaptability in dynamic financial environments [39], [34].

In conclusion, the integration of Agentic AI with machine learning represents a transformative approach to credit risk management in microfinance. The proposed system not only improves prediction accuracy but also enables proactive and autonomous decision-making, paving the way for next-generation intelligent financial systems.

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