AI PREDICTIVE MODEL FOR CREDIT UNDERWRITING

SYNOPSIS

- **Objective:** Develop an AI-Predictive Model for credit underwriting system to enhance loan approval predictions.
- **Data Collection & Preprocessing:** Handle missing values, feature encoding,outlier removal, normalization.
- **Results & Impact:** GBC improves accuracy, risk assessment, and decision-making, reducing false approvals and rejections.
- **Outcome:** A Streamlit-based AI app for loan predictions, EMI calculations, AI-driven financial advice, and report generation.

AI PREDICTIVE CREDIT UNDERWRITING VS. TRADITIONAL CREDIT UNDERWRITING

AI Predictive Credit Underwriting

- Automated & Data-Driven
- Real-Time Processing
- Advanced Risk Analysis
- Reduced Bias
- Self-Learning Models

Traditional Credit Underwriting

- Manual & Rule-Based
- Slower Processing
- Limited Data Usage
- Higher Risk of Bias
- Fixed Risk Assessment

ML MODELS

1. Logistic Regression
2. Decision Tree
3. Random Forest
4. AdaBoost
5. Naive Bayes
6. Gradient Boosting Classifier

TESTING AND EVALUATION

Comparison of Machine Learning Models

#	Model	Training Accuracy	Testing Accuracy	Overall Accuracy
1	Logistic Regression	92.28	92.28	92.28
2	Decision Tree	100.0	98.68	99.38
3	Random Forest	100.0	98.77	99.57
4	AdaBoost	97.36	97.27	97.36
5	Naive Bayes	86.93	93.69	86.88
6	Gradient Boosting	99.67	98.77	99.57

GRADIENT BOOSTING

Why Gradient Boosting is the Best Choice?

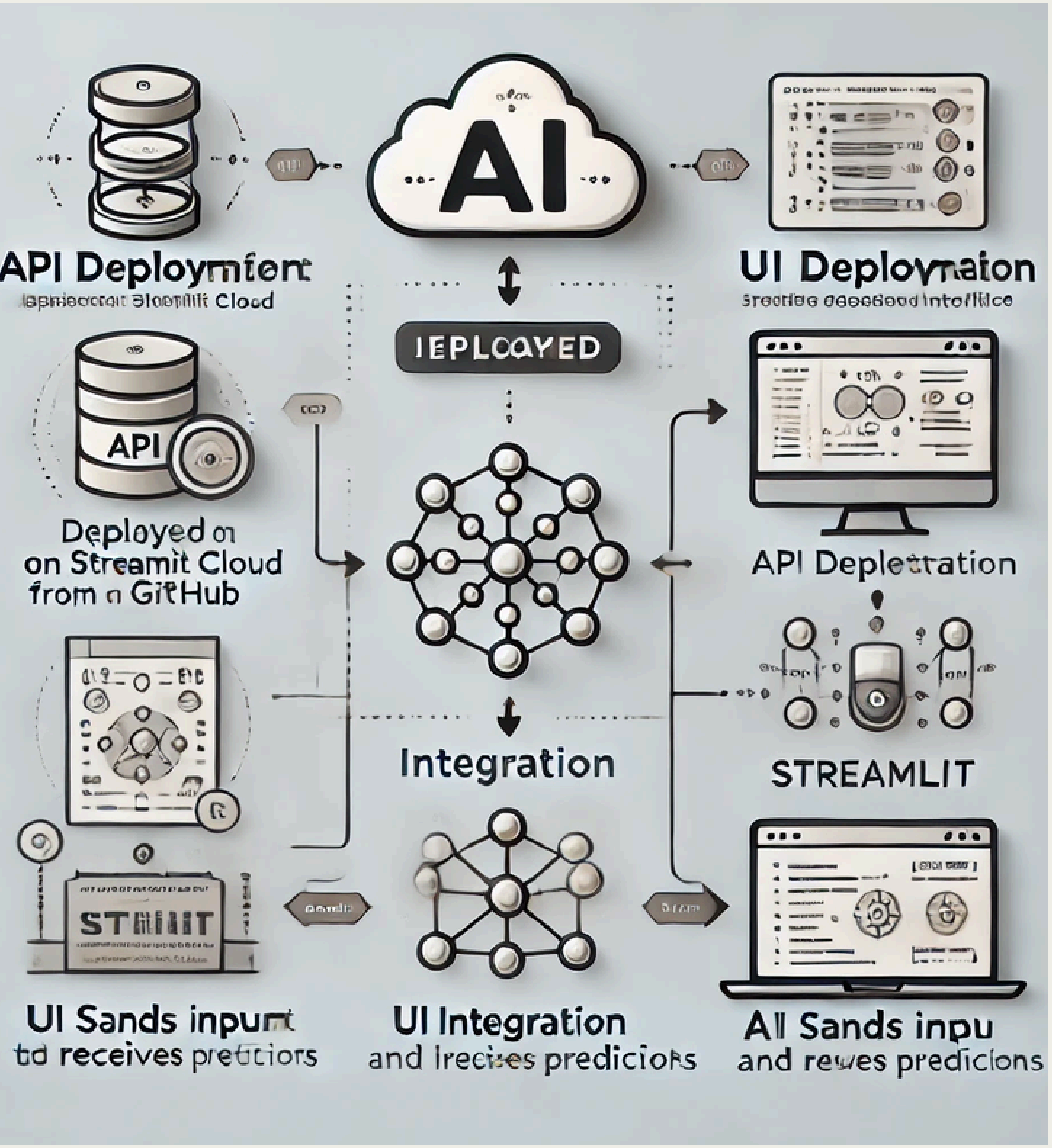
- Higher Accuracy & Performance
- Handles Complex Relationships
- Reduces Overfitting
- Feature Importance

RESULTS & PERFORMANCE METRICS

- **Accuracy:** 98.78%
- **Precision :** 98.90% (Class 0) , 98.65% (Class 1)
- **Recall :** 98.71% (Class 0) , 98.84% (Class 1)
- **F1-Score :** 98.80% (Class 0) , 98.75% (Class 1)
- **Confusion Matrix:**
  [[537, 7] , [6, 513]]

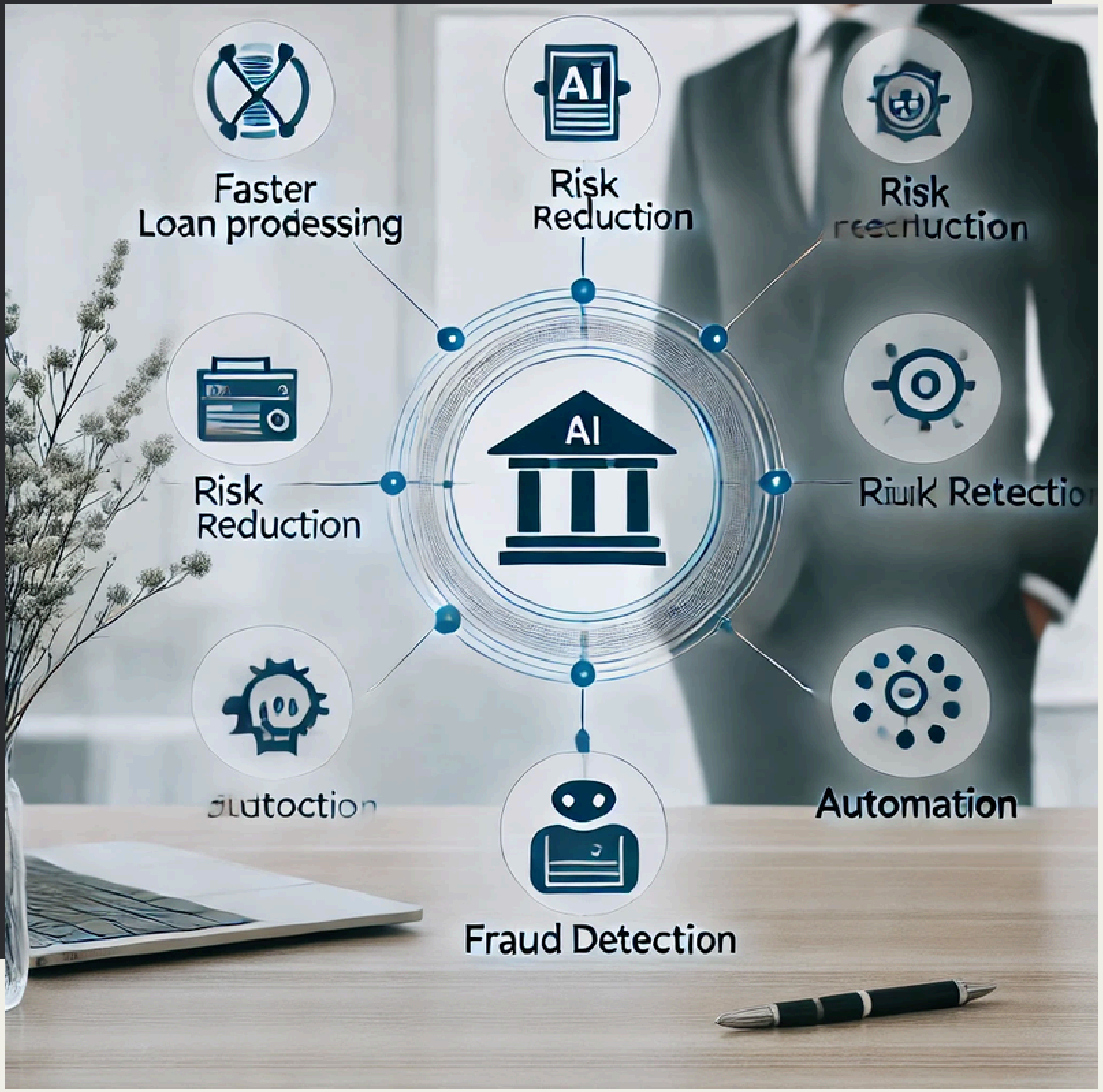
LIBRARIES

- **Programming Language:** Python
- Streamlit
- FPDF
- pandas
- matplotlib
- joblib
- transformers
- langdetect



IMPLEMENTATION DEPLOYMENT

1. API Deployment
2. UI Deployment
3. Integration
4. Testing



BENEFITS OF MODEL

🚀 Faster Loan Processing

📊 Data-Driven Decision Making

💰 Reduced Risk of Loan Defaults

🎯 High Accuracy in Predictions

📉 Lower Operational Costs

👥 Fair & Transparent Credit Scoring

📈 Continuous Improvement

🔗 Easy Integration with Existing Systems

CHALLENGES IN TRADITIONAL CREDIT UNDERWRITING

- ⏳ Time-Consuming Process
- 👥 Human Bias & Subjectivity
- 📄 Limited Data Utilization
- 💸 High Operational Costs
- ⚠️ Higher Risk of Loan Defaults
- 📊 Inability to Adapt to Market Trends
- 📉 Inconsistent Decision-Making
- 🔗 Lack of Integration with Modern Technologies

BUSINESS PROPOSITION & TARGET CUSTOMERS

- Faster Loan Approvals
- Lower Default Risks
- Cost Efficiency
- Fair & Unbiased Decisions
- Scalability & Adaptability

- Banks & Financial Institutions
- NBFCs (Non-Banking Financial Companies)
- Fintech Companies
- E-commerce & BNPL (Buy Now, Pay Later) Services
- Insurance & Investment Firms

CASE STUDY

Background

A leading NBFC faced challenges in loan approval delays, high default rates, and biased decision-making due to manual underwriting.

Problem Statement

- Lengthy loan approvals (7–10 days).
- High default rates due to poor risk assessment.
- Manual underwriting caused bias & inconsistency in approvals.
- Limited scalability to process high loan application volumes.

CONCLUSION

After evaluating multiple models, Decision Tree, Random Forest, and XGBoost achieved over 99% accuracy, proving their robustness. Logistic Regression performed poorly, indicating its unsuitability for complex credit risk patterns. These variations highlight the importance of model selection in underwriting. The final solution was deployed using Streamlit for an interactive user experience. This ensures a user-friendly interface for real-world applications.

Acknowledgement

We sincerely thank **Mr. Vivek Gautam sir** for his invaluable guidance and support throughout this internship. His constructive feedback was instrumental in the successful completion of our project.

We also extend our gratitude to **Infosys Springboard** for providing this amazing opportunity to apply our academic knowledge to real-world challenges.

This internship allowed us to gain hands-on experience in machine learning, data preprocessing, model deployment, and UI development, contributing significantly to our professional and personal growth.

REFERENCES & ONLINE RESOURCES

Online Resources:

- Scikit-learn Documentation: scikit-learn.org
- Pandas Documentation: pandas.pydata.org
- Kaggle: kaggle.com.

Articles & Learning Materials:

"A Comprehensive Guide to Regression in Machine Learning"

Streamlit Documentation: https://streamlit.io

Tools Used for Development & Deployment:

- YouTube Tutorials (YT)
- Google Search & Google Colab (AI & ML Experiments)
- VS Code (Code Editing & Debugging)

THANK YOU!