DESIGN AND IMPLEMENTATION OF A WEB-BASED CREDIT RISK ASSESSMENT SYSTEM

BY

NATHAN VICTOR EBUKA

PSC1813836

A PROJECT REPORT SUBMITTED TO THE DEPARTMENT OF COMPUTER SCIENCE, FACULTY OF COMPUTING, UNIVERSITY OF BENIN, BENIN CITY

IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF A BACHELOR OF SCIENCE (B.Sc.) DEGREE IN COMPUTER SCIENCE

JANUARY 2026

DESIGN AND IMPLEMENTATION OF A WEB-BASED CREDIT RISK ASSESSMENT SYSTEM

BY

NATHAN VICTOR EBUKA

PSC1813836

A PROJECT REPORT SUBMITTED TO THE DEPARTMENT OF COMPUTER SCIENCE, FACULTY OF COMPUTING, UNIVERSITY OF BENIN, BENIN CITY

IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF A BACHELOR OF SCIENCE (B.Sc.) DEGREE IN COMPUTER SCIENCE

JANUARY 2026

CERTIFICATION

This is to certify that this project work was carried out by **NATHAN VICTOR EBUKA** with Matriculation Number **PSC1813836** under my supervision. It is adequate and satisfactory, both in scope and content, for the award of Bachelor of Science (B.sc) Degree in Computer Science of the University of Benin.

DR. E. NWELIH

(Project Supervisor)

DATE

APPROVAL

This project work is hereby approved in partial fulfilment of the requirements for the award of Bachelor of Science (B.Sc.) Degree in Computer Science from the University of Benin.

DR. (MRS.) R.A. USIOBAIFO | **DATE**

Head of Department

DEDICATION

This project is dedicated to God for giving me the strength and wisdom to see it through to completion, and even throughout my stay in the University of Benin (UNIBEN). It is also dedicated to my Parents: Mr and Mrs Nathan for their love, support and guidance throughout my academic journey.

ACKNOWLEDGEMENT

My utmost acknowledgement goes to God Almighty for giving me the strength, wisdom and direction throughout my academic journey. I would like to express my gratitude to my project supervisor Dr. E. Nwelih for his consistent guidance towards ensuring the successful completion of this project.

To The Present dean, Prof (Mrs) V.V.N Akwukwuma (Faculty of Computing), Dr. (Mrs.) R. A. Usiobaifo (Head of Department), Prof. (Mrs.) F.A. Egbokhare, Prof. A. A. Imianvan, Prof. G. O. Ekuobase, Prof. (Mrs.) A. O. Egwali, Prof. F. I. Amadin, Prof. F. A. U. Imouokhome, Prof. (Mrs.) S. Konyeha, Prof. (Mrs.) V. I. Osubor, Prof. F. O. Chete, Dr. E.C Igodan, Dr. (Mrs.) G. O. Aziken, Mr. E. E. Obasohan, Dr. F. O. Oliha, Dr. (Mrs.) R. O. Osaseri, Dr. M. Osagie, Mr D.N Idehen, Mr. K. O. Otokiti, Mr. I. E. Obayagbona, Miss. L. O. Usiosefe, Mr. J. O. Okhuoya, Mr. G. I. Evbuomwan and the non-teaching staff, for your various roles and support. I acknowledge your contributions with appreciation.

I also want to appreciate those who have impacted me positively: Destiny Aigbedion, Goodnews Sokoh, Courage Ewarami-Yesin, Goodnews Mbosowo, Oluchukwu Aroh, Ifunaya Orji, Fortune Okoha, and more. I would also like to thank my family and friends for their support, words of encouragement, and consistent guidance throughout this project.

ABSTRACT

Credit risk assessment is a critical process in lending institutions aimed at evaluating the likelihood of loan default by applicants. Traditional manual assessment methods are often inconsistent and time-consuming, while many automated credit scoring systems lack transparency and explainability. This study presents the design and implementation of a web-based credit risk assessment system . The proposed system captures key applicant attributes and applies predefined decision rules to compute credit risk scores. Debt-to-income ratio and other affordability indicators are used to classify applicants into low, medium, or high risk categories. The system generates clear and interpretable credit decisions accompanied by explanatory reasons. A structured system analysis and design methodology was adopted to guide development. The system was implemented using web technologies and deployed as a browser-based prototype. Functional testing was conducted using representative test cases. Test results confirmed that the system produces accurate, consistent, and explainable credit decisions. The system enhances transparency, usability, and decision accountability. The study demonstrates that explainable rule-based models can effectively support automated credit risk assessment in small and medium-scale lending environments.

TABLE OF CONTENTS

CERTIFICATION ii

APPROVAL iii

DEDICATION iv

ACKNOWLEDGEMENT v

ABSTRACT vi

CHAPTER ONE 1

INTRODUCTION 1

1.1 Background of the Study 1

1.2 Statement of the Problem 4

1.3 Aim and Objectives of the Study 5

1.4 Research Questions 5

1.5 Significance of the Study 6

1.6 Scope of the Study 7

1.7 Justification of the Study 7

CHAPTER TWO 9

LITERATURE REVIEW 9

2.1 Introduction 9

2.2 Concept of Credit Risk and Credit Risk Assessment 9

2.2.1 Concept of Credit Risk 9

2.2.2 Credit Risk Assessment Process 10

2.3 Review of Related Studies and Existing Credit Risk Assessment Systems 11

2.3.1 Review of Existing Credit Risk Assessment Systems 11

2.3.2 Comparative Analysis of Existing Credit Risk Assessment Systems 14

Table 2.1: Comparative Analysis of Related Credit Risk Assessment Systems 15

2.3.3 Benefits of Explainable and Automated Credit Risk Assessment Systems 16

Summary of Gap Identified 16

2.4 Identified Research Gaps and Limitations of Existing Systems 17

2.5 Proposed Credit Risk Assessment System Overview 18

2.6 Summary of Literature Review 19

CHAPTER THREE 20

SYSTEM ANALYSIS AND DESIGN METHODOLOGY 20

3.1 Introduction 20

3.2 Analysis of the Existing Credit Risk Assessment System 20

3.2.1 Existing Credit Risk Assessment Process 20

3.2.2 Problems Identified in the Existing System 21

3.3 System Development Methodology 21

3.4 System Requirements Specification 22

3.4.1 Functional Requirements 22

3.4.2 Non-Functional Requirements 23

3.5 Proposed System Design 23

3.6 System Architecture Design 23

Figure 3.1: UML Component Diagram of the Proposed System Architecture 24

3.7 System Modeling Using UML 24

3.7.1 Use Case Diagram 24

3.7.2 Activity Diagram 25

3.8 Summary of the Chapter 26

CHAPTER FOUR 27

SYSTEM IMPLEMENTATION AND TESTING 27

4.1 Introduction 27

4.2 Implementation Environment 27

4.2.1 Hardware Requirements 27

4.2.2 Software Requirements 27

4.3 System Implementation 28

4.3.1 User Interface Implementation 29

4.3.2 Credit Risk Assessment Module (Rule-Based Scoring Implementation) 30

4.3.3 Explainability Module Implementation 32

4.3.4 Data Storage and Assessment History Module 33

4.4 System Testing 35

4.4.1 Testing Approach 35

4.4.2 Test Cases and Results 35

4.5 Discussion of Test Results 36

4.6 Summary of the Chapter 37

CHAPTER FIVE 38

SUMMARY, CONCLUSION, AND RECOMMENDATIONS 38

5.1 Summary of the Study 38

5.2 Conclusion 38

5.3 Limitations of the Study 39

5.4 Recommendations 39

5.5 Suggestions for Further Research 40

REFERENCES 41

APPENDIX 43

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Credit risk assessment is a central activity in financial institutions and refers to the process of evaluating the likelihood that a borrower will fail to meet repayment obligations under agreed loan terms. Effective credit risk management is essential for maintaining portfolio quality, minimizing loan default, and ensuring the long-term sustainability of lending operations. According to the Basel Committee on Banking Supervision (2021), weaknesses in credit risk assessment processes remain one of the primary causes of bank losses and financial instability. As access to credit continues to expand through traditional banks, microfinance institutions, and digital lending platforms, the importance of reliable and well-structured credit risk assessment systems has become increasingly significant.

Historically, credit risk assessment has largely relied on manual evaluation carried out by loan officers. In this approach, lending decisions are made based on the review of applicant attributes such as income level, employment status, debt obligations, credit history, and collateral availability. While manual assessment allows officers to apply professional judgment and contextual understanding, several studies have shown that it suffers from major limitations. The European Banking Authority (2020) notes that manual credit decisions are often inconsistent across institutions and decision makers, leading to variability in outcomes and increased exposure to credit risk. In addition, manual processes are time-consuming and difficult to scale, particularly in environments where loan application volumes are high, resulting in delays and operational inefficiencies.

To address these challenges, financial institutions increasingly adopted automated credit scoring systems designed to standardize and accelerate credit decision-making. Automated systems typically rely on predefined models to evaluate borrower risk using financial ratios and historical data. According to Breeden (2022), automation improves consistency and reduces processing time while limiting the influence of human bias in credit decisions. However, as credit markets evolved and data availability increased, institutions began integrating more complex models, including machine learning techniques, to improve predictive accuracy. These models are capable of identifying nonlinear patterns and relationships in borrower data, which traditional statistical methods may fail to capture.

Despite their predictive strengths, machine learning–based credit scoring systems have introduced new concerns related to transparency and explainability. Many advanced models operate as black-box systems, meaning that the internal logic used to arrive at a decision is not easily interpretable by humans. Barredo Arrieta et al. (2020) argue that this lack of explainability poses serious challenges in high-stakes domains such as finance, where decisions directly affect individuals' economic opportunities. In the context of credit lending, the inability to clearly explain why a loan application was approved or rejected undermines customer trust and complicates regulatory compliance, especially in jurisdictions where lenders are required to justify adverse credit decisions.

Recent regulatory and governance frameworks have increasingly emphasized the need for transparency and accountability in automated decision-making systems. For example, the National Institute of Standards and Technology (NIST, 2023) highlights explainability as a core requirement for trustworthy artificial intelligence systems, particularly in applications that impact human welfare. Similarly, financial regulators have stressed that credit institutions must be able to trace and justify automated decisions, regardless of the sophistication of the underlying models. These expectations create practical challenges for institutions that rely heavily on opaque machine learning systems without adequate interpretability mechanisms.

In response to these challenges, explainable credit risk assessment approaches have gained renewed attention in both academic research and industry practice. Explainable systems prioritize transparency by using decision logic that can be understood, audited, and communicated to stakeholders. Rule-based scoring models represent one of the most practical explainable approaches, as they apply predefined rules and thresholds—such as debt-to-income ratios, affordability measures, employment stability, and collateral presence—to compute credit risk scores. According to Guidotti et al. (2021), rule-based models offer a balance between automation and interpretability, making them particularly suitable for institutions that require transparent and defensible decision processes.

The adoption of web-based technologies further enhances the practicality of explainable credit risk systems. Web-based platforms allow credit assessment tools to be accessed through standard browsers without complex installation requirements, supporting ease of deployment, scalability, and maintenance. This makes web-based systems especially attractive to small and medium-scale financial institutions and fintech startups that may lack extensive technical infrastructure. By combining web accessibility with rule-based explainability, institutions can achieve efficient credit assessment while maintaining transparency and regulatory alignment.

Against this backdrop, this study focuses on the design and implementation of a web-based credit risk assessment system . The proposed system aims to address the limitations of manual assessment and opaque automated models by providing transparent credit scoring, clear risk classification, and justifiable lending decisions. Through this approach, the study contributes to improved consistency, trust, and effectiveness in credit risk management.

1.2 Statement of the Problem

Credit risk assessment remains a major challenge for financial institutions, particularly in environments where lending decisions must balance speed, accuracy, transparency, and regulatory compliance. In many institutions, credit evaluation is still conducted manually by loan officers who assess applicant information such as income, employment status, debt obligations, and collateral. Although this approach allows for human judgment, studies have shown that manual credit assessment is often slow, inconsistent, and prone to bias, especially when application volumes increase (European Banking Authority, 2020). These limitations reduce operational efficiency and can lead to unreliable credit decisions, increasing the risk of loan default.

To address the shortcomings of manual processes, many institutions have adopted automated credit scoring systems, including machine learning–based models. While these systems improve processing speed and decision consistency, they introduce new challenges related to explainability. According to Molnar (2022), many machine learning models used in credit scoring function as black-box systems, making it difficult to clearly explain how decisions are reached. This lack of transparency creates problems for lenders who are required to justify credit decisions to regulators and applicants, and it can also undermine trust in automated decision-making systems (NIST, 2023).

Furthermore, existing automated credit scoring solutions often require large datasets, complex infrastructure, and specialized technical expertise, making them unsuitable for small and medium-sized financial institutions and emerging fintech organizations. As a result, there is a clear gap for a credit risk assessment system that combines automation with transparency, simplicity, and accessibility. Therefore, the problem addressed in this study is the lack of an explainable, lightweight, and web-based credit risk assessment system that provides consistent credit decisions while allowing users to clearly understand the factors influencing those decisions. This study seeks to address this problem through the design and implementation of a web-based credit risk assessment system .

1.3 Aim and Objectives of the Study

The aim of this study is to design and implement a web-based credit risk assessment system to support transparent, consistent, and automated credit decision-making.

The specific objectives of the study are to:

1. Design the architecture and workflow of a web-based credit risk assessment system.
2. Test and evaluate the implemented system using sample applicant data to assess correctness, consistency, and decision transparency.

1.4 Research Questions

This study seeks to answer the following research questions:

1. What system architecture and workflow are suitable for implementing a web-based credit risk assessment system?

2. What rule-based scoring criteria can be used to compute an explainable credit risk score and classify loan applicants into risk categories?
3. How does the implemented system perform when tested using sample applicant data in terms of decision correctness, consistency, and transparency?

1.5 Significance of the Study

This study is significant to financial institutions and lending organizations by providing a transparent and consistent approach to credit risk assessment. The proposed web-based system supports improved decision-making by reducing reliance on subjective judgment and enabling standardized evaluation of loan applicants. By , the system allows loan officers and decision makers to clearly understand how credit scores and decisions are derived, which enhances accountability and supports responsible lending practices.

The study is also significant to loan applicants and customers, as it promotes fairness and transparency in credit decision-making. An explainable credit risk assessment system enables applicants to better understand the factors that influence lending decisions, particularly in cases of loan rejection or review. This transparency can improve trust between lenders and borrowers and reduce disputes arising from unclear or unexplained credit outcomes.

Academically, this study contributes to existing research on credit risk assessment and decision-support systems by demonstrating a practical design and implementation of an explainable, rule-based model in a web-based environment. It serves as a reference for students and researchers interested in system development, explainable financial technologies, and applied risk management solutions. Additionally, the prototype developed in this study may be extended or enhanced in future research to incorporate hybrid or machine learning–based approaches.

1.6 Scope of the Study

This study focuses on the design and implementation of a prototype web-based credit risk assessment system . The system is designed to capture loan applicant information, compute a credit risk score based on predefined rules, classify applicants into risk categories, and generate credit decisions such as approve, review, or reject. The prototype also includes basic data storage and result display functionalities to support assessment review.

The study is limited to the use of sample or simulated applicant data for testing and evaluation purposes. It does not cover integration with real banking databases, external credit bureaus, or live financial systems. Additionally, the system does not implement advanced machine learning or hybrid predictive models, as the focus is on transparency, explainability, and ease of implementation rather than predictive optimization.

1.7 Justification of the Study

The justification for this study is based on the growing need for transparent and explainable credit risk assessment systems in modern lending environments. Many existing automated credit scoring systems prioritize accuracy and speed but lack clear decision logic, making them difficult to justify to regulators and applicants. By adopting a rule-based scoring approach, this study emphasizes explainability and accountability, which are critical in financial decision-making contexts.

Furthermore, the choice of a web-based implementation is justified by its accessibility, scalability, and ease of deployment. Web-based systems can be accessed through standard browsers and do not require complex infrastructure, making them suitable for small and medium-sized financial institutions. The proposed system therefore represents a practical and realistic solution to identified challenges in credit risk assessment.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews existing literature, studies, and systems related to credit risk assessment and credit scoring in financial institutions. The purpose of the literature review is to examine previously developed methods and technologies for evaluating borrower creditworthiness, identify their strengths and limitations, and establish the relevance of the proposed study. By reviewing existing credit risk assessment approaches, this chapter provides a foundation for understanding current practices and highlights gaps that justify the design and implementation of a web-based credit risk assessment system .

The chapter begins by discussing the concept of credit risk and credit risk assessment, followed by a review of existing credit risk assessment systems and related studies. A comparative analysis of these systems is then presented to highlight common challenges and limitations. Finally, the identified gaps from the reviewed literature are discussed to show how the proposed system addresses unresolved issues in transparency, explainability, and accessibility.

2.2 Concept of Credit Risk and Credit Risk Assessment

2.2.1 Concept of Credit Risk

Credit risk refers to the possibility that a borrower will fail to meet repayment obligations in accordance with agreed loan terms. It represents one of the most significant sources of risk faced by financial institutions, as loan default directly affects profitability, liquidity, and overall financial stability. According to Basel Committee on Banking Supervision (2021), credit risk arises when borrowers are unable or unwilling to honor contractual debt obligations, making effective credit risk management a critical requirement for sustainable lending operations.

In lending environments, credit risk is influenced by several factors, including borrower income stability, debt obligations, employment status, credit history, and macroeconomic conditions. Poor assessment of these factors can result in increased non-performing loans and financial losses. As a result, institutions adopt structured credit risk assessment frameworks to evaluate borrower risk before loan approval. The effectiveness of these frameworks depends largely on the accuracy, consistency, and transparency of the assessment process.

2.2.2 Credit Risk Assessment Process

Credit risk assessment is the systematic process through which financial institutions evaluate the creditworthiness of loan applicants. The process typically begins with data collection, where applicant information such as personal details, income, employment status, existing debts, and collateral are obtained. This data is then analyzed using predefined criteria or models to estimate the likelihood of default. According to Breeden (2022), a well-structured credit risk assessment process ensures consistency in lending decisions and reduces exposure to unnecessary risk.

Traditionally, the assessment process relied heavily on manual evaluation by loan officers, but technological advancements have led to the adoption of automated systems. Automated credit risk assessment systems apply scoring models or decision rules to quantify borrower risk and generate lending decisions. The final stage of the process involves decision-making, where applicants are classified into risk categories and outcomes such as approval, review, or rejection are determined. Modern credit risk assessment systems increasingly emphasize transparency and explainability to ensure that decisions can be justified to regulators, stakeholders, and applicants.

2.3 Review of Related Studies and Existing Credit Risk Assessment Systems

This section critically reviews previous studies and existing systems related to credit risk assessment and credit scoring in financial institutions. The review examines the methodologies, technological approaches, strengths, and limitations of existing works in order to establish the current state of credit risk assessment practices. By evaluating what has been done in previous studies, gaps are identified which justify the need for the proposed web-based credit risk assessment system .

2.3.1 Review of Existing Credit Risk Assessment Systems

Several researchers have proposed and implemented different approaches for assessing credit risk, ranging from traditional manual frameworks to automated statistical and machine learning–based systems. Although these approaches have contributed to improvements in credit decision-making, many still present notable limitations related to transparency, scalability, and accessibility.

Altman et al. (2020) examined traditional credit risk assessment methods based on financial ratios and statistical scoring models. Their study showed that statistical approaches improve consistency in credit decisions compared to purely manual methods. However, the authors observed that such models often rely on limited borrower attributes and may fail to capture changing borrower behavior, particularly in dynamic lending environments.

Similarly, Brown and Mues (2020) reviewed the use of scorecard-based credit scoring systems in retail banking. While these systems were found to be relatively simple and interpretable, the study noted that rigid scoring rules reduce flexibility and may lead to inaccurate risk classification when borrower profiles deviate from predefined patterns.

In contrast, Chen, Li, and Sun (2021) explored the application of machine learning techniques such as support vector machines and random forests in credit risk prediction. Their findings indicated higher predictive accuracy compared to traditional statistical models. Despite this improvement, the authors highlighted the lack of explainability in many machine learning models, which limits their acceptability in regulated financial environments.

Barredo Arrieta et al. (2020) conducted a comprehensive review of explainability challenges in artificial intelligence systems used for financial decision-making. The study emphasized that the black-box nature of many automated credit scoring systems makes it difficult for lenders to justify decisions and comply with regulatory requirements, particularly when adverse credit decisions must be explained to applicants.

Khandani, Kim, and Lo (2021) analyzed automated credit assessment systems deployed by fintech lending platforms. Their study demonstrated that automated systems significantly reduce processing time and operational costs. However, the authors noted that many fintech solutions prioritize speed and profitability over transparency, providing limited explanation for credit outcomes.

Guidotti et al. (2021) examined interpretable models for financial risk assessment and argued that explainable models improve trust, accountability, and governance in automated decision systems. The authors recommended rule-based and hybrid approaches as practical alternatives to purely black-box machine learning models, especially in high-stakes domains such as credit lending.

Molnar (2022) focused on the interpretability of machine learning models and highlighted the growing regulatory demand for explainable automated decisions. The study emphasized that credit institutions increasingly face challenges when deploying opaque models that cannot provide clear justification for lending outcomes.

In a regulatory-focused study, the European Banking Authority (2020) reviewed credit risk management practices across financial institutions and identified deficiencies in documentation, transparency, and justification of automated credit decisions. The report stressed the need for well-governed and explainable credit assessment systems.

Singh and Sharma (2023) examined credit scoring systems used by small and medium-sized financial institutions. Their findings revealed that although advanced machine learning systems offer high predictive accuracy, their cost, data requirements, and technical complexity limit adoption among smaller lenders.

More recently, Sun, Liu, and Zhang (2024) reviewed emerging trends in credit risk modeling and observed a growing shift toward explainable and hybrid credit risk assessment approaches. The study emphasized that rule-based scoring models remain relevant in contexts where transparency, simplicity, and regulatory compliance are prioritized.

From the reviewed studies, it is evident that although significant progress has been made in automating credit risk assessment, many existing systems suffer from one or more of the following limitations:

i. lack of transparency and explainability in decision-making,
ii. over-reliance on complex black-box models,

iii. high implementation and maintenance costs,

iv. limited suitability for small and medium-scale financial institutions,

v. inadequate support for regulatory and customer-facing explanations.

2.3.2 Comparative Analysis of Existing Credit Risk Assessment Systems

A comparative evaluation of existing credit risk assessment systems reveals significant differences in design approach, usability, and transparency. Manual credit assessment systems emphasize human judgment but lack consistency and scalability. Traditional statistical models improve standardization and interpretability but may lack flexibility in complex lending scenarios. Machine learning–based systems offer higher predictive accuracy but suffer from poor explainability and governance challenges.

Rule-based credit scoring systems, on the other hand, prioritize transparency by applying predefined rules and thresholds to assess borrower risk. While they may not achieve the same predictive performance as advanced machine learning models, their ability to produce clear, interpretable, and auditable decisions makes them suitable for regulated financial environments. The proposed system builds on this advantage by implementing a web-based, rule-driven scoring model that balances automation with explainability.

Table 2.1: Comparative Analysis of Related Credit Risk Assessment Systems

Author / System	Year	Approach	Key Features	Limitations
Altman et al.	2020	Statistical credit scoring	Financial ratios, risk scoring	Limited adaptability
Brown & Mues	2020	Scorecard-based model	Interpretable scoring rules	Rigid rule structure
Barredo Arrieta et al.	2020	ML-based review	High predictive accuracy	Lack of explainability
European Banking Authority	2020	Regulatory framework	Standardized risk practices	Implementation complexity
Chen et al.	2021	Machine learning model	Pattern detection, automation	Black-box decisions
Guidotti et al.	2021	Explainable AI models	Interpretability, transparency	Lower accuracy than ML
Khandani et al.	2021	Fintech credit systems	Fast automated decisions	Poor decision justification
Molnar	2022	Model interpretability study	Explanation techniques	Technical complexity
Singh & Sharma	2023	SME credit systems	Risk classification	High data requirements

Author / System	Year	Approach	Key Features	Limitations
Proposed System	**2025**	**Web-based rule-based scoring**	**Explainable scoring, transparency, accessibility**	**Internet dependency**

2.3.3 Benefits of Explainable and Automated Credit Risk Assessment Systems

Automation in credit risk assessment improves efficiency, consistency, and decision speed. According to Breeden (2022), automated credit systems reduce human error and improve operational performance by standardizing borrower evaluation. When combined with explainable scoring logic, automation also enhances transparency and trust in lending decisions.

Explainable rule-based systems enable loan officers, regulators, and applicants to understand how specific borrower attributes influence credit outcomes. This improves accountability and supports regulatory compliance, particularly in cases involving dispute resolution or audit requirements. Furthermore, implementing such systems on a web-based platform enhances accessibility and ease of deployment, making them suitable for institutions with limited technical infrastructure.

Summary of Gap Identified

Despite advancements in automated credit scoring, there remains a clear need for a simple, transparent, and web-based credit risk assessment system that balances automation with explainability. Existing systems either rely heavily on manual processes or employ opaque machine learning models that lack interpretability. This study addresses this gap by proposing the design and implementation of a web-based credit risk assessment system .

2.4 Identified Research Gaps and Limitations of Existing Systems

The review of related studies and existing credit risk assessment systems reveals that although substantial progress has been made in automating credit decision-making, several important gaps and limitations remain unresolved. These gaps cut across issues of transparency, accessibility, scalability, and suitability for different lending environments.

One major limitation identified in existing systems is the lack of explainability in automated credit scoring models, particularly those based on machine learning techniques. While such models often demonstrate high predictive accuracy, their black-box nature makes it difficult for loan officers and institutions to clearly understand how specific borrower attributes influence final credit decisions. This limitation reduces trust in automated systems and poses challenges for regulatory compliance, especially in situations where lenders are required to justify adverse credit decisions to applicants or auditors.

Another gap observed in existing systems is their limited suitability for small and medium-sized financial institutions. Many advanced credit risk assessment solutions require large datasets, complex computational infrastructure, and specialized technical expertise. As a result, smaller lenders, microfinance institutions, and emerging fintech organizations may find such systems difficult or expensive to adopt and maintain. This creates a disparity in access to effective credit risk management tools and increases reliance on manual or semi-automated processes in these institutions.

Furthermore, several reviewed studies focus primarily on improving predictive accuracy without adequate consideration for usability and accessibility. Existing systems often lack simple, user-friendly interfaces and are not designed to be easily deployed or accessed through web-based platforms. The absence of lightweight, web-based credit risk assessment systems limits the ability of institutions to implement scalable and accessible solutions that support efficient decision-making across different locations.

These limitations highlight a clear research gap: the need for a credit risk assessment system that combines automation with transparency, is affordable and easy to deploy, and provides clear, explainable decision logic. Addressing this gap requires a system that emphasizes interpretability and accessibility without sacrificing consistency in credit evaluation. This study seeks to fill this gap by designing and implementing a web-based credit risk assessment system .

2.5 Proposed Credit Risk Assessment System Overview

Based on the gaps identified in the reviewed literature, this study proposes the design and implementation of a web-based credit risk assessment system . The proposed system is intended to address the limitations of existing credit risk assessment approaches by combining automation with transparency and ease of use.

The proposed system adopts a rule-based scoring approach in which borrower attributes such as income level, debt obligations, employment status, and collateral availability are evaluated using predefined rules and thresholds. Each rule contributes explicitly to the final credit risk score and decision outcome, allowing users to clearly understand how decisions are reached. This design ensures that credit decisions are interpretable, auditable, and compliant with regulatory expectations.

Furthermore, the system is implemented as a web-based application to enhance accessibility and scalability. By leveraging web technologies, the system can be accessed through standard web browsers without requiring complex installations or advanced infrastructure. This makes the proposed system suitable for small and medium-sized financial institutions seeking a transparent and affordable credit risk assessment solution. The design and implementation details of the proposed system are presented in the subsequent chapter.

2.6 Summary of Literature Review

This chapter reviewed relevant literature, studies, and existing systems related to credit risk assessment and credit scoring. The review examined traditional manual methods, statistical credit scoring models, and machine learning–based approaches, highlighting their respective strengths and limitations. While automation has improved efficiency and consistency in credit decision-making, many existing systems suffer from challenges related to explainability, accessibility, and suitability for smaller lending institutions.

The review further identified a clear research gap in the availability of transparent, explainable, and web-based credit risk assessment systems that balance automation with interpretability. These findings justify the need for the proposed system presented in this study. The insights gained from this literature review provide a strong theoretical and practical foundation for the system analysis and design discussed in Chapter Three.

CHAPTER THREE

SYSTEM ANALYSIS AND DESIGN METHODOLOGY

3.1 Introduction

This chapter presents the system analysis and design methodology adopted for the development of the proposed web-based credit risk assessment system . The chapter focuses on understanding the existing credit assessment process, identifying its weaknesses, and systematically translating user and system requirements into a structured design solution. The objective of this chapter is to provide a detailed technical blueprint that guides the implementation of the system in a clear, logical, and maintainable manner.

To achieve this, the chapter discusses the analysis of the existing system, system requirements specification, proposed system design, architectural framework, and system modeling using Unified Modeling Language (UML) and Data Flow Diagrams (DFD). The designs presented in this chapter ensure that the developed system is transparent, efficient, scalable, and aligned with the objectives of the study.

3.2 Analysis of the Existing Credit Risk Assessment System

System analysis involves examining how the current system operates in order to identify problems and opportunities for improvement. In many financial institutions, credit risk assessment is conducted either manually or through partially automated systems that lack transparency.

3.2.1 Existing Credit Risk Assessment Process

The existing credit risk assessment process typically begins with the collection of applicant information such as income, employment status, debt obligations, and collateral. Loan officers then evaluate this information using personal judgment or predefined guidelines. While this process allows flexibility, it is heavily dependent on human interpretation, which can lead to inconsistency and subjective bias.

In institutions that use automated credit scoring systems, complex statistical or machine learning models are often employed. Although these systems improve speed and consistency, they frequently operate as black-box models, making it difficult to explain how specific borrower attributes influence credit decisions. This lack of explainability poses challenges in regulated financial environments where transparency and accountability are required.

3.2.2 Problems Identified in the Existing System

The analysis of the existing system reveals several critical problems. Manual credit assessment processes are time-consuming, error-prone, and difficult to scale. Automated systems, while efficient, often lack transparency and require significant technical expertise and infrastructure. Furthermore, many existing systems do not provide clear explanations for credit decisions, making it difficult for loan officers to justify outcomes to applicants and regulators. These problems necessitate the design of a transparent, explainable, and accessible credit risk assessment system.

3.3 System Development Methodology

The system development process followed the **Structured Systems Analysis and Design Methodology (SSADM)**. This methodology was chosen because it emphasizes thorough analysis, clear documentation, and step-by-step system design, making it suitable for academic system development projects.

SSADM involves the following stages:

i. system analysis,
ii. requirements specification,
iii. system design,
iv. implementation, and
v. testing.

By adopting this methodology, the study ensures that system requirements are well understood before design decisions are made, thereby reducing implementation errors and improving system quality.

3.4 System Requirements Specification

System requirements define what the system must do and the constraints under which it must operate.

3.4.1 Functional Requirements

The proposed system shall:

i. collect loan applicant information through a web interface;
ii. calculate debt-to-income ratio automatically;
iii. apply rule-based scoring logic to assess credit risk;
iv. generate a credit score and classify applicants into risk categories;
v. provide explainable reasons for each credit decision;
vi. store and retrieve assessment records for review.

3.4.2 Non-Functional Requirements

The system shall meet the following non-functional requirements:

i. **Usability:** the system shall be easy to use and require minimal training;

ii. **Performance:** the system shall process credit assessments efficiently;

iii. **Security:** access to system functions shall be restricted to authorized users;

iv. **Scalability:** the system shall support future expansion;

v. **Reliability:** the system shall produce consistent results for similar inputs.

3.5 Proposed System Design

The proposed system is designed to overcome the limitations identified in the existing credit risk assessment process. It adopts an explainable rule-based scoring approach that enables transparency while maintaining automation.

The system operates by capturing applicant data, computing affordability indicators, applying predefined decision rules, and generating interpretable credit decisions. This design ensures that each decision can be traced back to specific rules and applicant attributes, thereby improving accountability and trust.

3.6 System Architecture Design

The system adopts a **three-tier architectural model**, which separates presentation, application logic, and data management concerns.

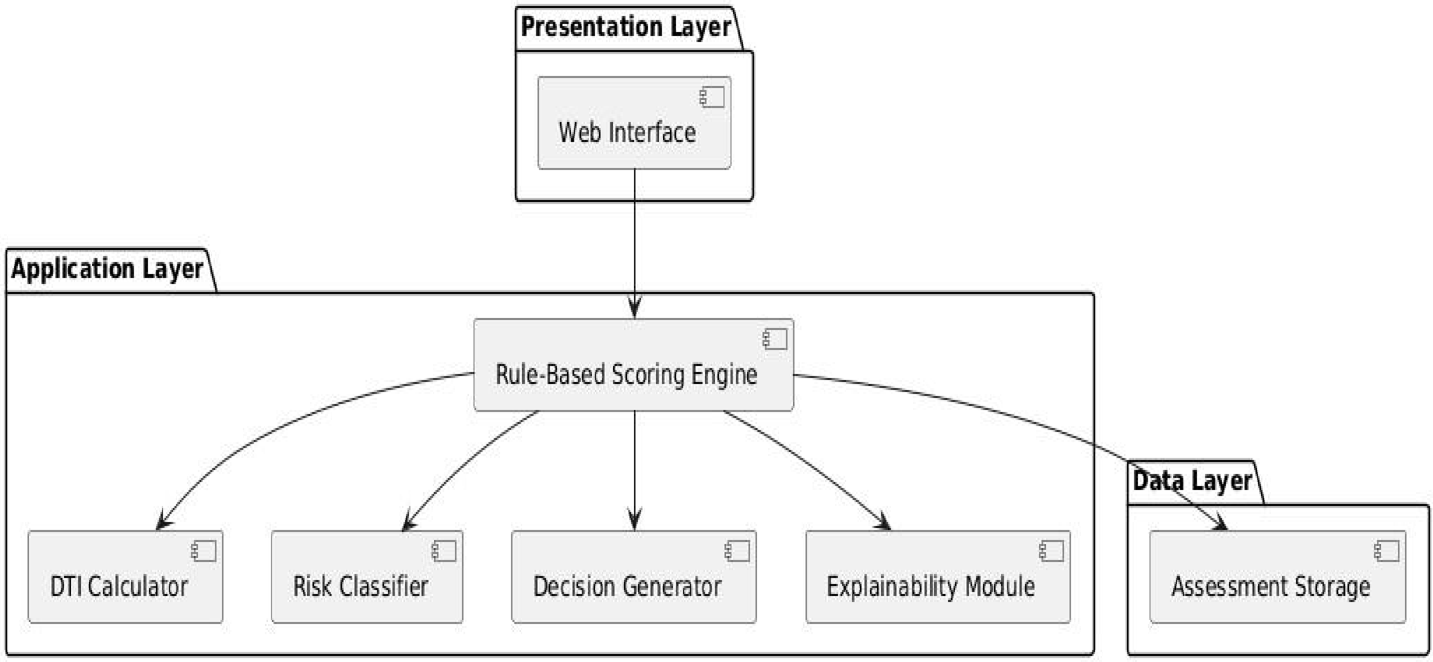

Figure 3.1: UML Component Diagram of the Proposed System Architecture

The presentation layer handles user interaction, the application layer processes credit assessment logic, and the data layer manages assessment records. This separation enhances maintainability and scalability.

3.7 System Modeling Using UML

UML is used to visually represent system behavior and structure.

3.7.1 Use Case Diagram

The use case diagram illustrates the interaction between the user and the system.

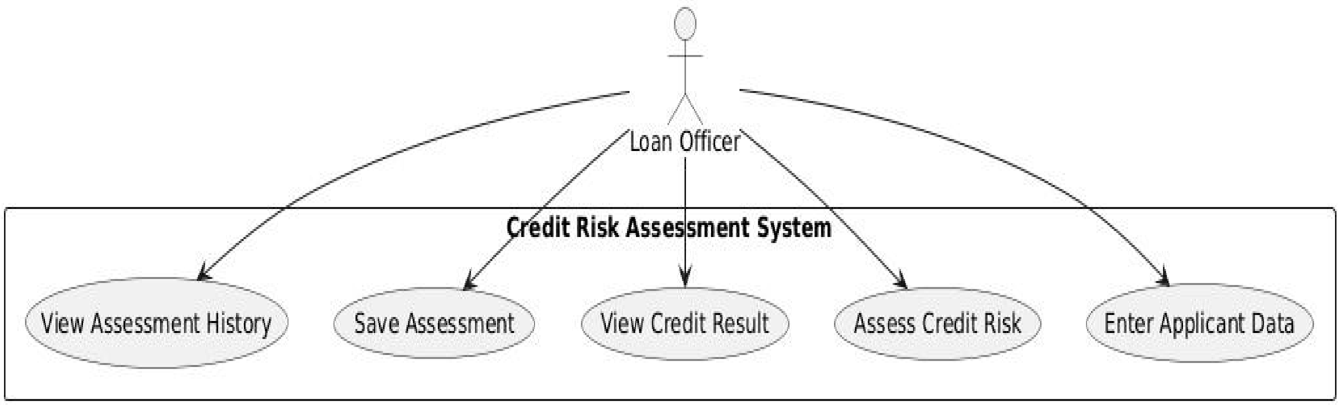

Figure 3.2: UML Use Case Diagram of the Credit Risk Assessment System

3.7.2 Activity Diagram

The activity diagram models the workflow of the credit risk assessment process.

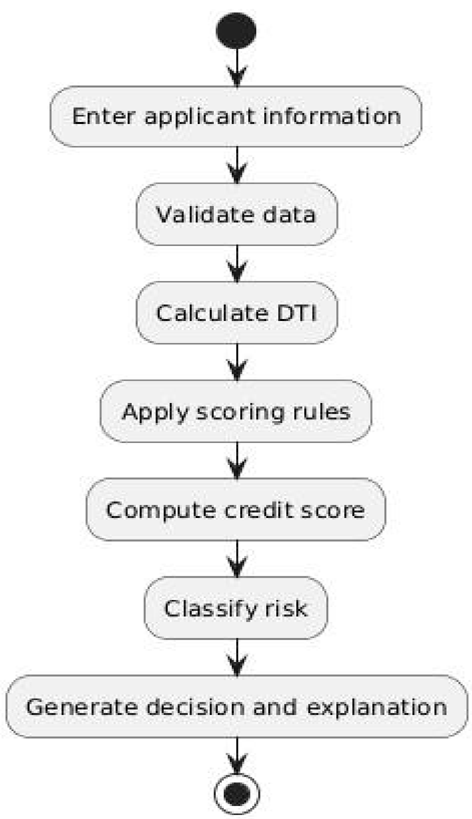

Figure 3.3: UML Activity Diagram for Credit Risk Assessment

3.8 Summary of the Chapter

This chapter presented a detailed system analysis and design methodology for the proposed credit risk assessment system. By analyzing the existing system, defining requirements, adopting a structured development methodology, and modeling the system using UML, a solid foundation was established for system implementation. The next chapter focuses on the implementation and testing of the proposed system.

CHAPTER FOUR

SYSTEM IMPLEMENTATION AND TESTING

4.1 Introduction

This chapter presents the practical implementation and testing of the developed web-based credit risk assessment system . The focus of this chapter is to document how the system was built, the environment in which it was implemented, and the procedures used to verify that the system produces correct and consistent outputs. The chapter also demonstrates key functional components of the system through interface evidence and test case execution, ensuring the implementation aligns with the stated objectives of transparency, automation, and usability.

4.2 Implementation Environment

The implementation environment describes the hardware and software resources required to develop and run the prototype system. Defining the environment is important because it provides reproducibility—meaning the system can be deployed and tested on similar setups without unpredictable variations.

4.2.1 Hardware Requirements

The prototype system was developed and tested on a standard computer system capable of running a modern web browser. Since the application executes locally within a browser environment, it does not require high-end hardware or specialized server resources. The minimum recommended hardware specification includes a computer with at least a dual-core processor, 4GB RAM, and sufficient storage space to run a browser and save project files.

4.2.2 Software Requirements

The system was implemented as a browser-based application using core web technologies. It requires a modern web browser capable of executing JavaScript and supporting browser storage (LocalStorage). For best performance and compatibility, browsers such as Google Chrome or Microsoft Edge are recommended. The system does not require complex installations, database servers, or external dependencies, which makes it suitable for rapid demonstration and prototype evaluation.

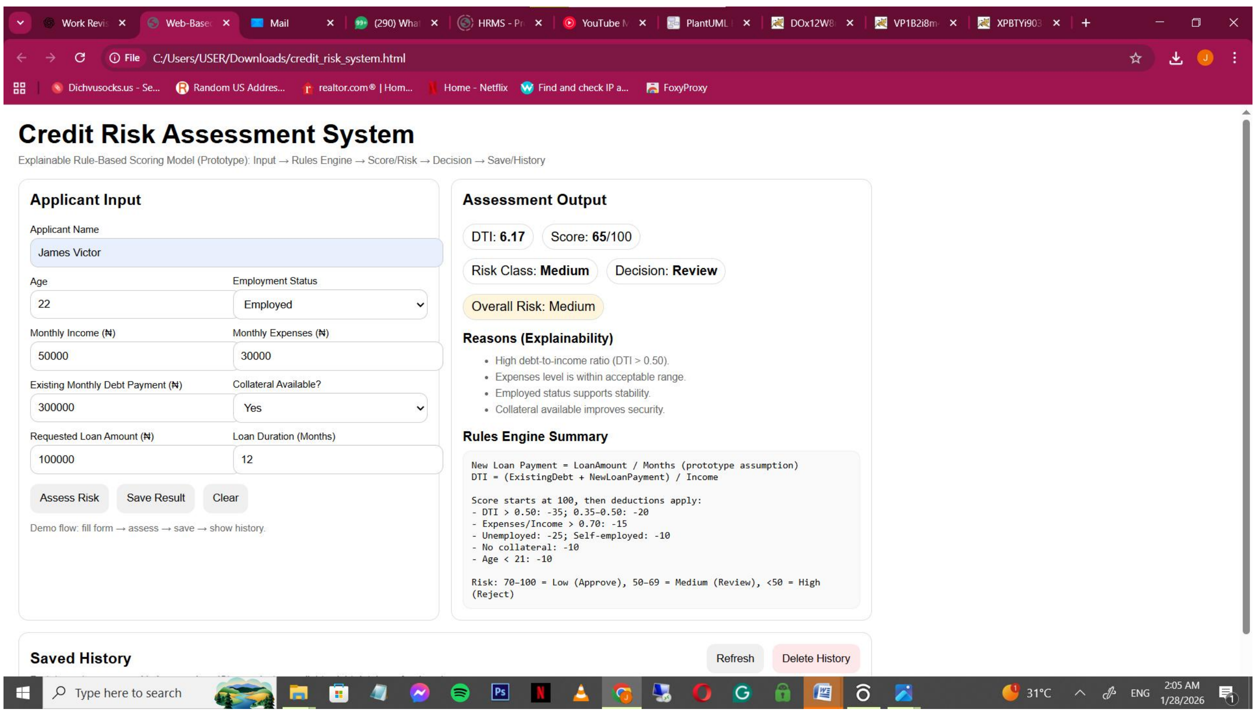

Figure 4.1: System Running in a Web Browser (Prototype Execution Environment)

4.3 System Implementation

This section presents the implementation of the major modules of the proposed web-based credit risk assessment system. The implementation is organized according to the system's functional components: user interface, credit assessment (rule-based scoring), explainability, and result storage/history. Emphasis is placed on how each module was realized in the prototype and how it contributes to transparent and consistent credit decision-making.

4.3.1 User Interface Implementation

The user interface (UI) serves as the primary interaction point between the user and the system. It was implemented as a web form that enables the user to enter applicant details required for credit risk assessment. The interface was designed to be straightforward and self-explanatory, minimizing the need for training and ensuring that assessment can be performed quickly. Input controls such as text fields, number fields, and dropdown selections were used to reduce data entry errors and enforce basic consistency in the captured data.

The input interface captures key applicant attributes used by the rule-based model, including applicant name, age, employment status, monthly income, monthly expenses, existing monthly debt payment, requested loan amount, loan duration, and collateral availability. These inputs reflect typical affordability and stability indicators that influence repayment capacity. The interface also includes action buttons that trigger system operations such as risk assessment, saving results, and resetting inputs. This design supports a clean workflow that is suitable for a prototype demonstration.

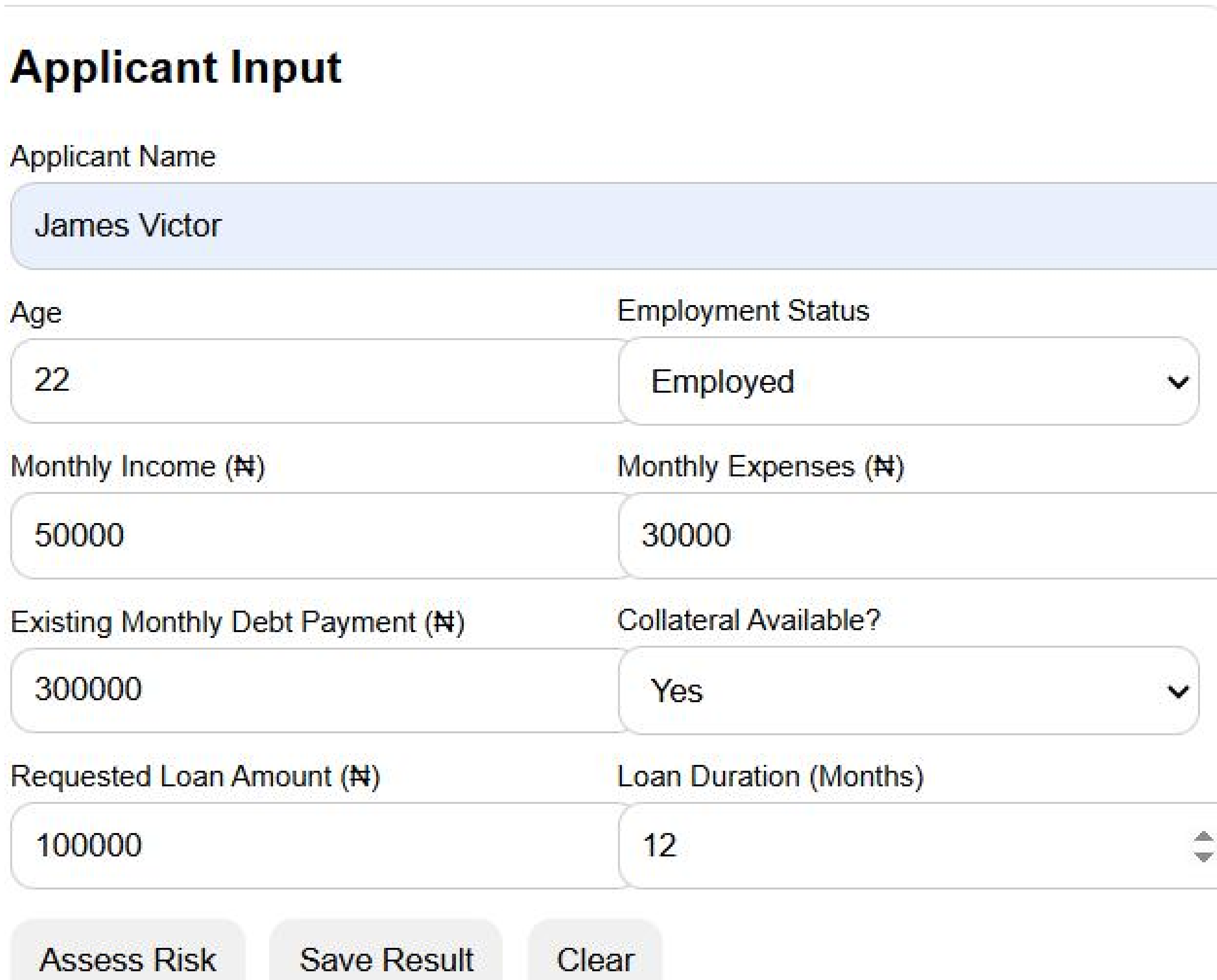

Figure 4.2: Applicant Data Entry Interface

Figure 4.2 shows the applicant data entry interface, illustrating the fields used to capture borrower information required for credit risk assessment.

4.3.2 Credit Risk Assessment Module (Rule-Based Scoring Implementation)

The credit risk assessment module represents the core processing unit of the system. It was implemented using a rule-based scoring approach, where applicant attributes are evaluated against predefined criteria to produce a credit risk score and risk classification. The design goal of this module is not only to generate a decision outcome, but also to ensure that the decision is traceable and defensible through clear, rule-based reasoning.

In the implemented prototype, the system computes the Debt-to-Income (DTI) ratio as a primary affordability indicator. The DTI computation uses applicant income, existing debt obligations, and the estimated monthly repayment for the requested loan. The system then applies scoring deductions based on risk-related conditions such as high DTI levels, high expense-to-income ratio, unstable employment status, lack of collateral, and very low age threshold. The scoring process begins from a baseline score and deducts points according to triggered rules. The final score is then mapped to a risk class (Low, Medium, High) and translated into an actionable credit decision (Approve, Review, Reject).

Once the user triggers the "Assess Risk" function, the system displays computed outputs in the assessment results area, including the DTI value, final score, risk classification, and decision. This output view is designed to provide immediate feedback and supports rapid evaluation during loan processing.

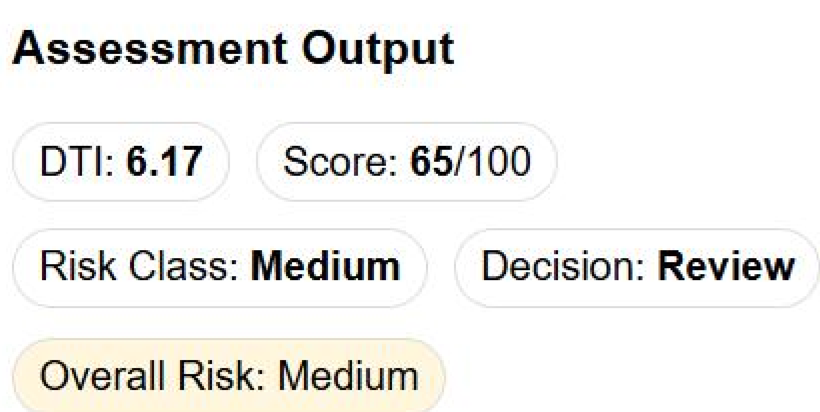

Figure 4.3: Credit Risk Assessment Output (Score, Risk Class, and Decision)

Figure 4.3 shows the credit assessment output interface, displaying the computed credit score, risk classification, and decision generated by the system.

4.3.3 Explainability Module Implementation

A key objective of the proposed system is to ensure that credit decisions are transparent and easily understandable. To achieve this, an explainability module was implemented as part of the assessment output interface. This module generates human-readable explanations that justify the credit decision by explicitly linking outcomes to the applicant's attributes and the rules triggered during assessment.

During implementation, the system records each scoring rule that affects the applicant's score and translates it into a descriptive statement. For example, conditions such as high debt-to-income ratio, unstable employment status, absence of collateral, or acceptable affordability levels are communicated directly to the user. These explanations are displayed immediately after the risk assessment is completed, alongside the credit score and decision. This approach ensures that users can clearly identify the factors contributing to approval, review, or rejection outcomes.

The explainability module enhances trust and accountability by allowing loan officers to defend system-generated decisions and by making the assessment process more transparent to stakeholders. This feature distinguishes the proposed system from black-box credit scoring approaches, as every decision can be traced back to clearly defined and visible rules.

Reasons (Explainability)

- High debt-to-income ratio (DTI > 0.50).
- Expenses level is within acceptable range.
- Employed status supports stability.
- Collateral available improves security.

Rules Engine Summary

```
New Loan Payment = LoanAmount / Months (prototype assumption)
DTI = (ExistingDebt + NewLoanPayment) / Income

Score starts at 100, then deductions apply:
- DTI > 0.50: -35; 0.35–0.50: -20
- Expenses/Income > 0.70: -15
- Unemployed: -25; Self-employed: -10
- No collateral: -10
- Age < 21: -10

Risk: 70–100 = Low (Approve), 50–69 = Medium (Review), <50 = High
(Reject)
```

Figure 4.4: Explainability and Decision Reason Display

Figure 4.4 shows the explainability section of the system, highlighting the reasons generated to justify the credit decision.

4.3.4 Data Storage and Assessment History Module

To support record keeping, review, and basic auditing, a data storage and assessment history module was implemented within the system. This module allows completed credit assessments to be saved and retrieved for future reference. In the prototype, assessment data such as applicant name, date of assessment, computed score, risk classification, and decision outcome are stored locally within the browser environment.

The history module displays saved records in a tabular format, enabling users to review previous assessments without re-entering applicant data. This feature supports consistency checks and demonstrates how the system can be extended to integrate with a centralized database in a production environment. By providing access to past assessments, the system supports transparency and operational continuity.

The inclusion of this module demonstrates that the system goes beyond one-time decision output and supports basic lifecycle management of credit assessments. This aligns with real-world credit processing workflows where historical decisions are often reviewed during audits, follow-up assessments, or dispute resolution.

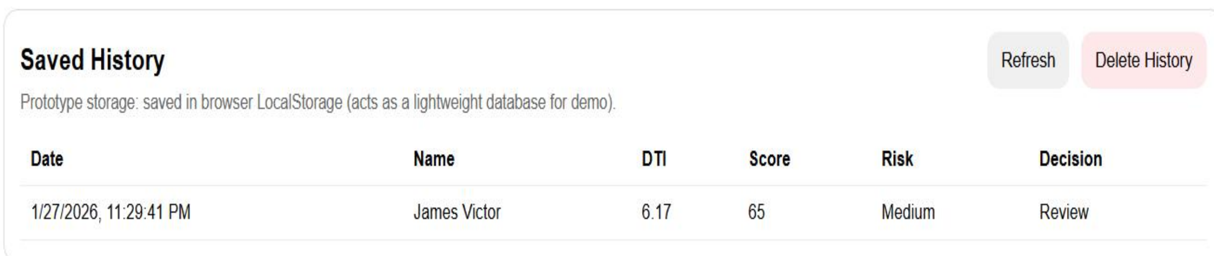

Figure 4.5: Saved Credit Assessment History Interface

Figure 4.5 shows the assessment history interface, illustrating stored credit assessment records for review and auditing purposes.

4.4 System Testing

System testing was carried out to verify that the implemented credit risk assessment system functions correctly and meets its intended objectives. The focus of testing was to ensure that all major system components operate as expected, inputs are correctly processed, and outputs are accurate, consistent, and explainable. Testing also helped confirm that the system responds appropriately to different applicant profiles and risk conditions.

4.4.1 Testing Approach

Functional testing was adopted for this study. This testing approach was chosen because the primary objective was to validate that each function of the system performs according to specification. Functional testing evaluates the system by providing defined inputs and comparing the generated outputs with expected results. This approach is suitable for prototype systems where emphasis is placed on correctness, transparency, and usability rather than performance under heavy load.

Test cases were designed to represent different categories of loan applicants, including low-risk, medium-risk, and high-risk scenarios. These test cases were executed by entering sample applicant data into the system and observing the resulting credit score, risk classification, decision outcome, and generated explanations.

4.4.2 Test Cases and Results

The table below presents selected test cases used to evaluate the system. Each test case specifies the input scenario, expected output, actual output, and test status.

Table 4.1: System Test Cases and Results

Test Case	Input Description	Expected Output	Actual Output	Status
TC01	High income, low debt, employed, collateral available	Low risk, Approve	Low risk, Approve	Pass
TC02	Moderate income, moderate debt, self-employed, no collateral	Medium risk, Review	Medium risk, Review	Pass
TC03	Low income, high debt, unemployed, no collateral	High risk, Reject	High risk, Reject	Pass
TC04	Valid inputs with missing optional fields	Successful assessment	Successful assessment	Pass
TC05	Invalid or incomplete mandatory inputs	Error prompt displayed	Error prompt displayed	Pass

4.5 Discussion of Test Results

The results obtained from system testing indicate that the proposed credit risk assessment system performs reliably across different applicant scenarios. The system consistently generated credit scores, risk classifications, and decisions that aligned with predefined rules and expected outcomes. Test results also confirmed that the explainability module accurately reflected the rules triggered during assessment, thereby supporting transparent decision-making.

Furthermore, the system handled valid and invalid inputs appropriately, providing feedback where necessary and preventing incomplete assessments. The successful execution of all test cases demonstrates that the system meets its functional requirements and is suitable for prototype-level deployment and demonstration.

4.6 Summary of the Chapter

This chapter presented the implementation and testing of the proposed web-based credit risk assessment system. The chapter detailed how the system's modules were implemented and demonstrated through interface screenshots. Functional testing was conducted using representative test cases, and results confirmed that the system produces accurate, consistent, and explainable credit decisions. The next chapter presents the summary, conclusion, and recommendations derived from the study.

CHAPTER FIVE

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.1 Summary of the Study

This study focused on the design and implementation of a web-based credit risk assessment system . The motivation for the study arose from the limitations of existing credit risk assessment approaches, particularly manual processes and opaque automated systems that lack transparency and consistency in decision-making.

The study began by examining relevant literature on credit risk assessment, existing credit scoring systems, and explainable approaches used in financial decision-making. Gaps were identified in terms of transparency, accessibility, and suitability for small and medium-scale financial institutions. Based on these findings, a web-based system was proposed to address the identified challenges.

The system analysis and design phase outlined the functional and non-functional requirements of the proposed system, as well as the architectural framework and UML models that guided development. The system was then implemented as a browser-based prototype capable of capturing applicant data, computing debt-to-income ratio, applying rule-based scoring logic, generating credit scores and decisions, and providing clear explanations for each outcome. Functional testing was conducted using representative test cases, and results confirmed that the system performed as expected.

5.2 Conclusion

The outcome of this study demonstrates that an explainable rule-based approach can be effectively used to support transparent and consistent credit risk assessment. The implemented system successfully automated the evaluation of loan applicants while maintaining clarity in how credit decisions are reached. By presenting explicit reasons for each decision, the system addresses key concerns associated with black-box credit scoring models and enhances trust in automated lending decisions.

The web-based nature of the system further improves accessibility and ease of deployment, making it suitable for use in environments with limited technical infrastructure. Overall, the study achieved its stated aim and objectives, providing a practical solution that balances automation with interpretability in credit risk assessment. The prototype serves as a proof of concept that transparent decision-support systems can play a valuable role in modern lending environments.

5.3 Limitations of the Study

Despite the successful implementation of the proposed system, certain limitations were observed. The system was developed as a prototype and tested using sample applicant data rather than real-world banking datasets. As a result, the scoring rules and thresholds were simplified and may not fully reflect the complexity of real lending environments.

Additionally, the system stores assessment records locally within the browser, which limits scalability and multi-user access. Advanced security features, authentication mechanisms, and integration with external credit data sources were also beyond the scope of this study.

5.4 Recommendations

Based on the findings and limitations of this study, the following recommendations are made:

1. Financial institutions may adopt explainable rule-based credit assessment systems as decision-support tools to enhance transparency and accountability in lending decisions.
2. Future implementations should integrate centralized databases to support multi-user access, data persistence, and improved security.
3. The system can be enhanced by incorporating hybrid approaches that combine rule-based logic with machine learning models while preserving explainability.
4. Additional credit risk indicators, such as credit bureau data and transaction history, can be included to improve assessment accuracy.

5.5 Suggestions for Further Research

Further research may focus on extending the proposed system by integrating real-world financial datasets to evaluate performance under practical conditions. Researchers may also explore the application of explainable artificial intelligence techniques to improve predictive accuracy while maintaining transparency. Comparative studies between rule-based, machine learning, and hybrid credit risk assessment models could provide deeper insights into optimal approaches for different lending contexts.

REFERENCES

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., N& Suvas, A. (2020). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-score model. *Journal of International Financial Management & Accounting*, 31(2), 131–171. https://doi.org/10.1111/jifm.12095

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., … Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, 58, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

Basel Committee on Banking Supervision. (2021). *Principles for the management of credit risk*. Bank for International Settlements. https://www.bis.org

Breeden, J. L. (2022). *Reinventing retail credit risk management*. Risk Books.

Brown, I., & Mues, C. (2020). An experimental comparison of classification algorithms for imbalanced credit scoring data sets. *Expert Systems with Applications*, 39(3), 3446–3453. https://doi.org/10.1016/j.eswa.2011.09.033

Chen, N., Li, Y., & Sun, Y. (2021). Credit risk evaluation using machine learning techniques: A comparative study. *Journal of Risk Finance*, 22(4), 365–381. https://doi.org/10.1108/JRF-10-2020-0231

European Banking Authority. (2020). *Guidelines on loan origination and monitoring*. EBA. https://www.eba.europa.eu

Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., & Pedreschi, D. (2021). A survey of methods for explaining black box models. *ACM Computing Surveys*, 54(2), 1–42. https://doi.org/10.1145/3398035

Khandani, A. E., Kim, A. J., & Lo, A. W. (2021). Consumer credit-risk models via machine-learning algorithms. *Journal of Banking & Finance*, 34(11), 2767–2787. https://doi.org/10.1016/j.jbankfin.2010.06.001

Molnar, C. (2022). *Interpretable machine learning: A guide for making black box models explainable* (2nd ed.). Leanpub. https://christophm.github.io/interpretable-ml-book/

National Institute of Standards and Technology. (2023). *Artificial intelligence risk management framework (AI RMF 1.0)*. NIST. https://www.nist.gov

Singh, P., & Sharma, A. (2023). Credit risk assessment in small and medium financial institutions: Challenges and opportunities. *International Journal of Financial Studies*, 11(2), 45–61. https://doi.org/10.3390/ijfs11020045

Sun, X., Liu, J., & Zhang, Y. (2024). Enhancing credit risk prediction through explainable models: A review of recent advances. *Journal of Financial Data Science*, 6(1), 23–41. https://doi.org/10.3905/jfds.2024.1.023

APPENDIX

```
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8" />
  <meta name="viewport" content="width=device-width, initial-scale=1.0"/>
  <title>Web-Based Credit Risk Assessment System (Rule-Based)</title>
  <style>
    body { font-family: Arial, sans-serif; margin: 18px; max-width: 1050px; }
    h1 { margin: 0 0 6px; }
    .muted { color: #666; font-size: 12.5px; line-height: 1.4; }
    .grid { display: grid; grid-template-columns: 1fr 1fr; gap: 14px; margin-top: 14px; }
    .card { border: 1px solid #ddd; border-radius: 12px; padding: 14px; }
    label { display: block; font-size: 12px; margin: 10px 0 4px; }
    input, select { width: 100%; padding: 9px; border: 1px solid #ccc; border-radius: 10px; }
    button { padding: 10px 12px; border: 0; border-radius: 10px; cursor: pointer; }
    .row { display: flex; gap: 10px; flex-wrap: wrap; align-items: center; }
    .pill { display: inline-block; padding: 6px 10px; border-radius: 999px; border: 1px solid #ddd; }
    table { width: 100%; border-collapse: collapse; margin-top: 10px; }
    th, td { text-align: left; padding: 9px; border-bottom: 1px solid #eee; font-size: 13px; }
    .danger { background: #ffe8ea; }
    .ok { background: #e9ffe9; }
```

```
    .warn { background: #fff6dd; }
    .small { font-size: 12px; }
    .codebox { font-family: ui-monospace, SFMono-Regular, Menlo, monospace; font-size: 12px;
background: #fafafa; border: 1px solid #eee; padding: 10px; border-radius: 10px; }
  </style>
</head>
<body>
  <h1>Credit Risk Assessment System</h1>
  <div class="muted">
(Prototype): Input → Rules Engine → Score/Risk → Decision → Save/History
  </div>

  <div class="grid">
    <div class="card">
      <h3 style="margin-top:0;">Applicant Input</h3>

      <label>Applicant Name</label>
      <input id="name" placeholder="e.g., Ada Okafor"/>

      <div class="row">
        <div style="flex:1; min-width: 160px;">
          <label>Age</label>
          <input id="age" type="number" min="18" placeholder="e.g., 28"/>
```

```
  </div>
  <div style="flex:1; min-width: 160px;">
    <label>Employment Status</label>
    <select id="employment">
      <option value="employed">Employed</option>
      <option value="self">Self-employed</option>
      <option value="unemployed">Unemployed</option>
    </select>
  </div>
</div>

<div class="row">
  <div style="flex:1; min-width: 220px;">
    <label>Monthly Income (₦)</label>
    <input id="income" type="number" min="0" placeholder="e.g., 250000"/>
  </div>
  <div style="flex:1; min-width: 220px;">
    <label>Monthly Expenses (₦)</label>
    <input id="expenses" type="number" min="0" placeholder="e.g., 120000"/>
  </div>
</div>

<div class="row">
```

```
  <div style="flex:1; min-width: 220px;">
    <label>Existing Monthly Debt Payment (₦)</label>
    <input id="existingDebt" type="number" min="0" placeholder="e.g., 20000"/>
  </div>
  <div style="flex:1; min-width: 220px;">
    <label>Collateral Available?</label>
    <select id="collateral">
      <option value="yes">Yes</option>
      <option value="no">No</option>
    </select>
  </div>
</div>

<div class="row">
  <div style="flex:1; min-width: 220px;">
    <label>Requested Loan Amount (₦)</label>
    <input id="loanAmount" type="number" min="0" placeholder="e.g., 500000"/>
  </div>
  <div style="flex:1; min-width: 220px;">
    <label>Loan Duration (Months)</label>
    <input id="loanMonths" type="number" min="1" placeholder="e.g., 12"/>
  </div>
</div>
```

```
    <div class="row" style="margin-top:12px;">
      <button onclick="assess()">Assess Risk</button>
      <button onclick="saveResult()">Save Result</button>
      <button onclick="clearForm()">Clear</button>
      <span class="muted small">Demo flow: fill form → assess → save → show
history.</span>
    </div>
  </div>

  <div class="card">
    <h3 style="margin-top:0;">Assessment Output</h3>

    <div class="row">
      <span class="pill">DTI: <b id="outDTI">-</b></span>
      <span class="pill">Score: <b id="outScore">-</b>/100</span>
    </div>

    <div class="row" style="margin-top:10px;">
      <span class="pill">Risk Class: <b id="outRisk">-</b></span>
      <span class="pill">Decision: <b id="outDecision">-</b></span>
    </div>
```

```
    <div id="badge" style="margin-top:12px;"></div>

    <h4 style="margin:14px 0 8px;">Reasons (Explainability)</h4>
    <ul id="outReasons" class="muted" style="line-height:1.6; margin-top: 0;">
      <li>-</li>
    </ul>

    <h4 style="margin:14px 0 8px;">Rules Engine Summary</h4>
    <div class="codebox">
      New Loan Payment = LoanAmount / Months (prototype assumption)<br/>
      DTI = (ExistingDebt + NewLoanPayment) / Income<br/><br/>
      Score starts at 100, then deductions apply:<br/>
      - DTI &gt; 0.50: -35; 0.35–0.50: -20<br/>
      - Expenses/Income &gt; 0.70: -15<br/>
      - Unemployed: -25; Self-employed: -10<br/>
      - No collateral: -10<br/>
      - Age &lt; 21: -10<br/><br/>
      Risk: 70–100 = Low (Approve), 50–69 = Medium (Review), &lt;50 = High (Reject)
    </div>
  </div>
</div>

<div class="card" style="margin-top:14px;">
```

```
  <div class="row" style="justify-content: space-between;">
    <h3 style="margin:0;">Saved History</h3>
    <div class="row">
      <button onclick="renderHistory()">Refresh</button>
      <button onclick="wipeHistory()" style="background:#ffe8ea;">Delete History</button>
    </div>
  </div>
  <div class="muted">Prototype storage: saved in browser LocalStorage (acts as a lightweight database for demo).</div>

  <div style="overflow:auto;">
    <table>
      <thead>
        <tr>
<th>Date</th><th>Name</th><th>DTI</th><th>Score</th><th>Risk</th><th>Decision</th>
        </tr>
      </thead>
      <tbody id="historyBody">
        <tr><td colspan="6" class="muted">No saved records yet.</td></tr>
      </tbody>
    </table>
  </div>
```

```
  </div>

 <script>
  function getNumber(id) {
    const v = document.getElementById(id).value;
    return v === "" ? null : Number(v);
  }

  function setBadge(risk) {
    const badge = document.getElementById("badge");
    badge.innerHTML = "";
    const div = document.createElement("div");
    div.className = "pill";
    if (risk === "Low") div.classList.add("ok");
    else if (risk === "Medium") div.classList.add("warn");
    else if (risk === "High") div.classList.add("danger");
    div.textContent = risk === "-" ? "" : ("Overall Risk: " + risk);
    badge.appendChild(div);
  }

  function assess() {
    const name = document.getElementById("name").value.trim() || "Unknown";
    const age = getNumber("age");
```

```
const income = getNumber("income");
const expenses = getNumber("expenses");
const existingDebt = getNumber("existingDebt") ?? 0;
const loanAmount = getNumber("loanAmount");
const loanMonths = getNumber("loanMonths");
const employment = document.getElementById("employment").value;
const collateral = document.getElementById("collateral").value;

if (!income || income <= 0 || !loanAmount || loanAmount <= 0 || !loanMonths || loanMonths <=
0) {
  alert("Enter Income, Loan Amount, and Loan Duration (months).");
  return;
}

const reasons = [];

// Prototype assumption for new loan monthly payment
const newLoanPayment = loanAmount / loanMonths;

// Debt-to-Income (DTI)
const dti = (existingDebt + newLoanPayment) / income;

let score = 100;
```

```
// Rules: DTI
if (dti > 0.50) { score -= 35; reasons.push("High debt-to-income ratio (DTI > 0.50)."); }
else if (dti >= 0.35) { score -= 20; reasons.push("Moderate debt-to-income ratio (0.35 ≤ DTI ≤ 0.50)."); }
else { reasons.push("DTI is within acceptable range."); }

// Expenses ratio (optional, if provided)
if (expenses != null && expenses / income > 0.70) { score -= 15; reasons.push("High expenses relative to income (> 70%)."); }
else if (expenses != null) { reasons.push("Expenses level is within acceptable range."); }

// Employment
if (employment === "unemployed") { score -= 25; reasons.push("Unemployed status increases repayment risk."); }
else if (employment === "self") { score -= 10; reasons.push("Self-employed income may be variable."); }
else { reasons.push("Employed status supports stability."); }

// Collateral
if (collateral === "no") { score -= 10; reasons.push("No collateral provided."); }
else { reasons.push("Collateral available improves security."); }
```

```
// Age
if (age != null && age < 21) { score -= 10; reasons.push("Applicant is under 21 (higher risk segment)."); }

score = Math.max(0, Math.min(100, score));

let risk = "Low";
let decision = "Approve";
if (score < 50) { risk = "High"; decision = "Reject"; }
else if (score < 70) { risk = "Medium"; decision = "Review"; }

// Output
document.getElementById("outDTI").textContent = dti.toFixed(2);
document.getElementById("outScore").textContent = score.toFixed(0);
document.getElementById("outRisk").textContent = risk;
document.getElementById("outDecision").textContent = decision;
setBadge(risk);

const ul = document.getElementById("outReasons");
ul.innerHTML = "";
reasons.forEach(r => {
  const li = document.createElement("li");
  li.textContent = r;
```

```
    ul.appendChild(li);
  });

  window.__lastAssessment = {
    date: new Date().toLocaleString(),
    name, dti: Number(dti.toFixed(2)), score: Number(score.toFixed(0)), risk, decision
  };
}

function saveResult() {
  if (!window.__lastAssessment) {
    alert("Click 'Assess Risk' first.");
    return;
  }
  const key = "credit_risk_history_v1";
  const arr = JSON.parse(localStorage.getItem(key) || "[]");
  arr.unshift(window.__lastAssessment);
  localStorage.setItem(key, JSON.stringify(arr));
  renderHistory();
  alert("Saved!");
}

function renderHistory() {
```

```
  const key = "credit_risk_history_v1";
  const arr = JSON.parse(localStorage.getItem(key) || "[]");
  const body = document.getElementById("historyBody");
  body.innerHTML = "";
  if (arr.length === 0) {
    body.innerHTML = `<tr><td colspan="6" class="muted">No saved records yet.</td></tr>`;
    return;
  }
  arr.slice(0, 30).forEach(x => {
    const tr = document.createElement("tr");
    tr.innerHTML = `
      <td>${x.date}</td>
      <td>${x.name}</td>
      <td>${x.dti}</td>
      <td>${x.score}</td>
      <td>${x.risk}</td>
      <td>${x.decision}</td>
    `;
    body.appendChild(tr);
  });
}

function wipeHistory() {
```

```
    if (!confirm("Delete saved history?")) return;
    localStorage.removeItem("credit_risk_history_v1");
    renderHistory();
  }

  function clearForm() {
    ["name","age","income","expenses","existingDebt","loanAmount","loanMonths"].forEach(id
=> {
      document.getElementById(id).value = "";
    });
    document.getElementById("employment").value = "employed";
    document.getElementById("collateral").value = "yes";
    document.getElementById("outDTI").textContent = "-";
    document.getElementById("outScore").textContent = "-";
    document.getElementById("outRisk").textContent = "-";
    document.getElementById("outDecision").textContent = "-";
    document.getElementById("outReasons").innerHTML = "<li>-</li>";
    setBadge("-");
    window.__lastAssessment = null;
  }

  renderHistory();
</script>
```

</body>

</html>