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A Systems Engineering Approach for Credit Risk Assessment in Agricultural AIoT Data

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Abstract

Evaluation of credit risk is an essential element in the process of granting credit at the Rural Credit Bank (RCB), particularly for the Micro, Small, and Medium Enterprises (MSMEs) sector in rural agriculture. The conventional approach based on historical data in finance is often unable to reflect the real conditions of agricultural business, which are influenced by environmental and productivity factors. Research: This aim: To design a methodology for evaluating risk more comprehensively by utilizing agricultural data based on Agricultural Artificial Intelligence of Things (AIoT) through the Systems Engineering Process (SEP) approach. The SEP methodology serves as a framework for systematic work, encompassing Requirements Analysis, System Design, Implementation, Testing, Deployment, and Maintenance stages to ensure the developed system fulfils the RCB technical and operational data needs. Data from agricultural sensors integrated into an in-system computer support risk analysis and credit decisions in a more objective, data-driven way. Approach: This allows the use of real-time, contextual non-financial data as a supplement to conventional financial data. Design results show that SEP implementation can produce a system evaluation risk structure that is structured, adaptive, and aligned with the RCB business processes. This potential increase in accuracy evaluation risk reduces subjectivity in officer credit and supports improvements in inclusion in finance for the MSME sector and rural agriculture.

***Keywords**: System Engineering Process; Credit Risk Assessment; Agricultural AIoT; Rural MSMEs*

1. Introduction

Rural Micro, Small, and Medium Enterprises (MSMEs) play a strategic role in supporting the national economy, especially in the agricultural sector. However, despite access to formal financing at credit banks, people still face various obstacles, especially in the assessment and risk credit processes. Assessment models for risk credit are generally based on historical financial data, are holistic, circular, and static, and therefore cannot accurately reflect the real condition of an agricultural business, which is greatly influenced by factors such as the environment, production, and seasonal dynamics. The limitations of the data pose a risk to height perception, lead to low inclusion in finance, and increase the potential for inaccurate decision-making in credit for rural MSMEs.

Problems mainly in context. This is not yet an availability system evaluation risk credit capable of systematically and sustainably integrating non-financial data. Rural Credit Bank (RCB) still faces difficulty in processing agricultural data of an olistic, real-time, and distributed nature, such as land condition, weather, productivity, and cultivation patterns. On the other hand, the use of Artificial Intelligence of Things (AioT) technology in the agricultural sector is not yet optimized as a source of strategic information for credit decision-making. The absence of framework engineering, structured systems, and development system evaluation often leads to partial, less integrated systems that are difficult to adapt to change, particularly in rural business environments.

Liu et al.'s research used an experimental approach based on deep learning, developing a Hierarchical Attention-based Feature Selection and Fusion (HAFF) model that integrates mechanism-level and view-level attention for feature selection and multi-source feature fusion based on cost data acquisition [1]. Model performance was evaluated using the Area Under the Curve (AUC) to measure the ability to predict credit risk with reduced features. An approach different from that applied [2], who adopted reinforcement learning via deep Q-learning in scheme simulation learning, which is sustainable in the manufacturing sector but has limitations in list credit. The model was validated by comparing its accuracy with conventional machine learning algorithms and was equipped with interpretability analysis using SHAP and LIME. Meanwhile, Goldmann et al. implemented a stacked hybrid olistic method; moreover, they previously used time series classification to balance the data for daily customers, then added the classification output as a feature to the XGBoost model, which was evaluated using AUC and analyzed for interpretability using SHAP [3].

Approaches based on predictive supervised learning and optimization are also used in several studies. applies the LightGBM algorithm, combined with clever optimization techniques, within a stage-based methodology that covers data normalization, processing of olistic finance borrowers, model training, and performance comparisons with logistic regression and support vector machine (SVM) to evaluate the model's stability and accuracy [4]. Zhao and Tian developed a cost-sensitive learning approach by designing an asymmetric loss function, QTSELF, for the SVM model, optimizing its parameters with the Adam optimizer, and evaluating performance using AUC and G-mean to handle class imbalance [5]. Besides that, built a system warning early risk credit with an AI-based modeling convolutional neural network (CNN), where the selection is done using principal component analysis (PCA) and grey correlation analysis, as well as financial and non- financial data processing done in a way separated before classification risk [6].

Several studies have developed hybrid methodologies that combine AI modeling with optimization and multicriteria decision-making. Bao et al proposed a multicriteria management model. Risk credit chain real estate supply with integrate genetic algorithm (GA) and SVM, as well as enter modified KMV model and analysis of the text, to increase the accuracy of predicting failed pay [7]. Wang et al use the Aspiration–Ability–Action (3A) framework with a multicriteria decision-making methodology, where fuzzy Delphi is used for selection, game-theoretic weighting for determining weights, and the DQGRA–MARCOS method for ranking risk quantitatively [8]. On the other hand, applied a quantitative approach combining integer linear programming, intelligent artificial intelligence, and Pareto analysis to optimize the inspection process for the Letter of Credit document using international bank operational data [9].

Approach automation and analysis efficiency also appear in the methodology study of risk credit. Zhou applies automated machine learning (AutoML) using the EasyDL platform to automate data cleaning, feature selection, and optimal model selection for evaluating credit risk based on marketing and customer data [10]. Huang et al used a quantitative, dynamic network data envelopment analysis (DEA) in three stages, along with the Malmquist Index Model, to analyze the impact of economic uncertainty on efficiency in the business and commercial banking credit sector, based on a banking panel dataset for 2016–2022 [11]. In addition, Combined a hidden Markov model (HMM) and latent Dirichlet allocation (LDA) to develop a methodology that leverages time-series data and text from financial time series and companies to predict risk in the security network [12].

Outside approach, experimental; some studies use a methodological synthesis and analysis approach. Alvi et al. (2024) applied a five-stage systematic literature review to hundreds of articles published in the 2015–2024 period to identify the evolution of methodologies and shifts in predictive models [13]. Zhang and Yu use a combined PRISMA approach, with CiteSpace for analysis of listic use, map algorithms, data characteristics, and trends, and for methodology evaluation and risk credit consumers [14]. Meanwhile, Xu and Chen adopted a qualitative-normative methodology by analyzing regulations, policies, and practices of justice, and the study's implications for the application of AI, blockchain, and LegalTech in risk management and personal credit [15]. Zhao et al conducted a study using quantitative panel data regression and equilibrium models, including multi-sector general equilibrium models. To analyze the connection between the transformations of smart, fintech, and green growth through the mechanism of credit allocation [16].

The study by Li focuses on developing risk-oriented, dynamic predictive models for parent finance groups in China that are facing systemic consequences of digital expansion and transformation [17]. The methodology integrates holistic financial and non-financial reporting regulations with the Analytic Hierarchy Process (AHP) and a coefficient-based efficiency approach, as well as a fuzzy-logic-based evaluation for mapping risk, liquidity, assets, and credit adaptively over time. Meanwhile that, Khalil et al study automation inspection document Letter of Credit (LC) in trading international through perspective transformation organization AI based methodology study they nature conceptual-applicative with combine framework Technology OrganizationEnvironment (TOE) and Technology Acceptance Model (TAM), which are strengthened by the review literature systematic, insightful experts and analysis studies case For formulate map road realistic AI adoption in olisti regulation [18]. In a different context, Kengpol and Klunngien develop an approach to evaluate risk-intelligent prediction of COVID-19 in Thailand, with a methodology integrating a Deep Neural Network (DNN) and a Tunicate Swarm Algorithm (TSA) to optimize the model training process. The prediction results were furthermore mapped using Data Envelopment Analysis (DEA) to classify regional risk levels based on time and distance of emergency cases [19]. As for Wang and Fu's research on the connection between FinTech development and green credit distribution banking, with put management risk as a mediating variable. Methodology: panel data regression on commercial

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banks in China, 2017–2023, with measurement of FinTech level done through text mining of annual bank reports on digital transformation intensity as the objective [20].

Approaches based on alternative data and digital technology are also demonstrated in several studies. Darwiesh et al developed an intelligent system for managing stock market risks that utilizes social media data as a source of non-traditional risk information [21]. In the methodology study, they use Natural Language Processing (NLP), including large-scale data cleansing, tokenization, lemmatization, and the development of a lexicon-based risk model to extract perception risk from social media users, which are then analyzed in the context of the NASDAQ stock market. Furthermore, Luo and Zhang expand the evaluation of risk credit company technology with an enterprise analysis olistic from report research olistic. The methodology combines Bidirectional Encoder Representations from Transformers (BERT) and Bidirectional Long Short-Term Memory (BiLSTM) models to extract holistic text, which is then used as additional input to the Random Forest model to improve credit risk classification accuracy [22].

On the other hand, Jovanovic et al propose a framework for automated work evaluation credit that emphasizes privacy and transparency by integrating blockchain, federated learning, and explainable AI. The methodology study utilizes a blockchain consortium for recording distributed learning, federated for collaboration across olisti without sharing raw data, as well as optimization via quadratic convexity in global model aggregation [23]. Finally, Yang et al analyze the impact of adopting manufacturing intelligence on the behavior of credit-trading companies using a difference-in-differences (DID) approach. Methodology: This applied to company panel data on A-share manufacturing in China, which was combined with an analysis text report and annual reports to identify digital transformation, enabling testing of the causal relationship between manufacturing intelligence and dynamic credit trade [24].

The study on risk, credit, and finance in rural areas shows a dominance of a data-driven approach, quantitative-based modeling, and machine learning. Chai et al investigated risk credit farmers by developing a hybrid ensemble ADASYN–LCE model to address data imbalance, which was then combined with SHAP to increase the interpretability of predictions, and evaluated using AUC and model ranking [25]. Focus on sector financing rural areas was also studied by Rao et al through the development of a two-stage modified cost-sensitive Random Forest for evaluating risk in P2P lending credit "Three Rurals", using web-crawled data and a comparison-based performance metric: cost error and AUC [26]. In that, Alzamora et al test various deep machine learning algorithms for credit in micro rural areas in Peru through an experimental comparison and K-fold cross-validation, with LightGBM achieving the highest accuracy [27]. An approach macro to finance rural areas development, carried out by Wang and Zhang, who analyzed the impact of the digital economy's development on rural inclusion. Fixed effects and difference-in-differences (DID) panel data regression were used on sub-provincial data in China [28]. Furthermore, Zheng and Liu examine the role of the digital economy as a moderating variable in the relationship between agricultural lending and income inequality between villages and cities, using a quantitative panel analysis with OLS, fixed effects, and instrumental variables to address potential endogeneity [29].

Risk assessment and digital transformation are also expanded to the banking and technology financial sectors. Ge et al study the influence of digital finance on behavior, focusing on small- and medium-sized bank risks, using panel regression with mediation analysis and an IV-SLS endogeneity test on banking data from term olisti [30]. A more comprehensive approach was implemented by He et al through a combination of text mining, annual reports, dynamic panel regression, System GMM, and two-stage DEA to analyze the connection between digital transformation and the profitability of commercial banks in rural areas [31]. In the context of development finance in rural areas, Zhao and Wang use a two-panel analysis with an endurance-test-based lag variable to examine the impact of digital transformation, while accounting for factor moderation by infrastructure and demographics [32]. Approach-based technology was also demonstrated by Bi and Liang, who developed an assessment model for risk finance based on big data and IoT, using regression and decision tree methods on customer behavioral data [33]. At the institutional level, Chen et al propose a holistic system evaluation environment credit rural use combination of AHP–Entropy and Cloud Model, to handle uncertainty at the macro and micro [34], while Li et al apply a method of multi-criteria group decision making, CPT–TODIM based on fuzzy type-2 numbers For choosing a cooperative reform model credit rural areas [35]. Alternative and temporal data perspectives are reviewed by Otieno et al through a qualitative-exploratory approach, based on interviews and FGDs [36], and by Gao et al, who developed a risk model for credit micro-improved and tested an LSTM-based approach in an experimental setting [37]. Lastly, Kumar et al and Karami and Igbokwe each used systematic, structured literature reviews to synthesize the development of deep machine learning and big data technology evaluation risk credit in rural areas [38] [39].

The main problems lie in the distribution of credit in rural areas. This is due to the unpreparedness of assessment models for conventional risk at the Rural Credit Bank (RCB), which still relies heavily on historical data. Finance is static, so it fails to represent real business dynamics and influence factors such as farming, the environment, and productivity. A significant research gap was found in the availability of a system evaluation capable of integrating non-financial data systematically and sustainably. Although the literature has explored intelligent approaches such as deep learning and reinforcement learning, hybrid models, and development systems, these approaches are often partial, less integrated, and challenging to adapt due to the absence of a structured framework for systems engineering in the development process. In addition, leverage Artificial Intelligence of Things (AIoT) to inform real-time strategic credit decisions. Not yet completely optimized.

Newness (novelty) of research. This lies in the proposal: a methodology evaluation of risk-based credit in a holistic, systems-engineering approach. Unlike previous studies, the majority focused on predictive modeling experiments, rather than pure research. This integrates agricultural data-based AIoT directly into the lifecycle development of a system, including analysis and maintenance needs. Renewal: this also includes the use of real-time environmental and production data on agricultural products as an analytical basis for intelligent artificial systems to produce information that is more risk-informed, accurate, objective, and contextual, compared to relying solely on conventional financial report data.

As a solution to the problem, research this offer framework and systematically design a risk-adaptive credit system to transform the environment in rural business areas, including adoption-stage analysis, system design, implementation, testing, and methodology. This allows RCB to process scattered, complex agricultural data into a measurable risk indicator. This solution is expected to improve quality by making informed decisions, strengthening financial risk management within the institution, and promoting inclusive and sustainable financing for agricultural development in rural areas.

2. Research Methods

Study this adopted framework, the systematic Systems Engineering Process (SEP) work, to transform raw data from agricultural sensors into accurate decision-making. Methodology: This ensures that the system being built not only advances on a technical level but is also relevant to the needs of Rural Credit Bank (RCB) operations and the unique characteristics of the MSME sector in agriculture. Stages in Engineering Process Methodology System for Credit Risk Assessment of Rural MSMEs Using Agricultural AIoT Data in Rural Credit Banks:

Figure 1. Systems Engineering Process (SEP) for evaluating risk village MSME credit using AIoT data in agriculture

1. Requirements Analysis
   Requirements Analysis in research. The aim is to identify and formulate the need for system evaluation, risk alignment, and credit, with reference to the operations of Rural Credit Banks (RCB) and the dynamics of the MSME sector in agriculture. Stage This focuses on mapping stakeholders' interests, in particular, analyst RCB credit, against a capable system that processes raw data from agricultural sensors (Agricultural AIoT) into information that is accurate, reliable, and easy to interpret for risk management. Analysis needs to cover functional requirements in the collection, integration, and processing of agricultural data, as well as non-functional requirements such as accuracy, reliability, ease of use, and suitability for limited infrastructure in

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rural banking areas. Thus, the system is designed as a tool to support decisions that uphold the principle of caution in the distribution of agricultural MSME credit.

2. System Design
   System Design in research. This focused on designing an architecture for evaluating system architecture, risk, and credit, capable of integrating Agricultural AIoT data with RCB business processes. Stage This covers the design structure module main, starting with agricultural sensor data acquisition, pre-processing, and feature extraction, and culminating in module analytics that produce indicators of risk in the MSME credit sector of agriculture. The system design also takes into account interoperability with existing RCB information and ensures that data flows and outputs are transparent and easy to interpret by analysts. With this approach, the system is designed as an efficient, scalable, and appropriate decision-support system, with limitations due to infrastructure constraints in rural banking.
3. Implementation
   Implementation in research. This is a stage of realizing a design system to form a functional prototype that integrates Agricultural AIoT data with a mechanism for evaluating risk and RCB credit. At this stage, this module includes agricultural sensor data acquisition, data preprocessing, and algorithmic analytics for the extraction of indicator risk credit, implemented and tested incrementally. The implementation process should address limitations in infrastructure banking for rural areas, so that the system is developed with an efficient, modular, and easy-to-operate approach by the analysts' credit. Thus, the system can produce recommendations that are accurate and applicable to credit within the context of RCB operations.
4. Testing
   Testing in research. The aim is to ensure that the system evaluation risk credit Agricultural AIoT-based functioning in accordance with the set needs and produces reliable output. Stage: This covers testing the functionality of the entire module system, testing module integration, and evaluating the system's performance in processing agricultural sensor data, which serves as an indicator of risk for MSME credit. In addition, testing was conducted with a considered operational RCB to evaluate accuracy, consistency, and the ease of interpreting results by analysts. Test results are used as a basis for an improvement system before implementation in rural environmental banking.
5. Deployment
   Deployment in research. This is a stage implementation system evaluation risk credit Agricultural AIoT-based in the environment operational of the Rural Credit Bank (RCB). At this stage, this system is integrated with work processes and systems, RCB information that has been walking, and customized with condition infrastructure banking in rural areas. The deployment process also includes configuring the system, adjusting operational parameters, and socializing its use as an analyst credit tool, so that it can function as a support tool for effective decision-making. With the implementation of this system, it is expected to support decision-making in the MSME credit sector in agriculture in a more objective, accurate, and sustainable way.
6. Maintenance
   Maintenance in research. This focuses on efforts, maintenance, and improvement of the system evaluation risk credit. Agricultural AIoT- based after applied in the environment RCB operations. Stage This covers periodic monitoring of performance systems, with data updates and analytical models to keep them aligned with changes in agricultural and MSME behavior, and to handle emerging technical issues during use. The maintenance process also ensures a sustainable system, operational stability, and consistent quality results, as well as risk credit evaluation, so that the system remains relevant and reliable in support of long-term decision-making on RCB credit.

3. Results and Discussions

3.1. *Assessment process risk MSME credit*

Assessment of the risk process for MSME credit and the agriculture sector at the Tapin Sejahtera Rural Credit Bank (RCB) at the moment. This is still done manually and conventionally, depending on the combination of evaluation, administrative, observation field, and subjective officer credit. System: This follows the principle of caution banking (prudential banking); however, it is not yet fully supported by the system's analytics- or integrated digital-technology-based capabilities.

The process begins with customer submissions of credit applications, both from MSME actors and farmers, which are submitted directly at the BPR office. Customers require document administration in the form of an identity self, a letter of information, a business or land ownership, income notes, and guarantees held. In the agricultural sector, documents are generally still simple and not standardized, such as letters of information from the head village or a group of farmers. Hence, data quality depends heavily on the completeness and honesty of customer information.

Figure 2. Assessment process risk MSME credit and sectors agriculture at the Tapin Sejahtera Rural Credit Bank (RCB)

Next, the Account Officer (AO) or officer credit conducts an eligibility analysis using approach 5C (Character, Capacity, Capital, Collateral, and Condition of Economy). Evaluation of customer character is done through live interviews, historical connections with customers and the bank, as well as informal information from the environment around. At this stage, the institution and experience officer credit hold role is dominant, mainly due to limitations in historical data and the lack of an automated credit scoring system.

Evaluation of capacity and capability pay is done using a manual cash flow calculation based on estimated income from the business or the harvest. For MSMEs, the estimated income is often not supported by financial reports. At the same time, for the agricultural sector, analysis is greatly influenced by factors such as seasonality, weather, and volatile commodity prices. Conditions: This creates height uncertainty risk, especially in financing agriculture.

The next is a survey field (on-the-spot), where officers credit visit location MSME businesses or land agriculture customers. The aim is to verify the existence of companies, the condition of assets, and the suitability information conveyed to customers. Survey results are recorded in a handwritten report, without structured digital documentation, which complicates long-term data tracking and risk evaluation.

After the analysis and survey are completed, the officer compiles the proposal credit, which is then submitted to the committee credit or RCB leaders for approval. The decision-making process is semi-subjective because there is no standardized quantitative risk assessment model yet. Financial considerations heavily influence credit decisions: managerial experience, prior experience, and tolerance for bank risk.

In a way, the overall system evaluation risk of MSME and agricultural credit at RCB Tapin Sejahtera, which is still manual, has several limitations, including:
1. dependence is high on the subjective officer credit,
2. limitations of historical data and digital documentation,
3. difficulty in measuring the risk sector of agriculture accurately, and
4. Potential inconsistency in taking a credit decision.

Condition: This shows that although the manual system is still relevant for context local and personal relationships with customers, it requires a strengthened system evaluation, greater risk, structured, objective, and data- based use increase quality portfolio credit as well as pressing risk credit problematic (Non-Performing Loan/NPL), especially in MSME financing and the financial sector agriculture.

Based on the assessment process, credit the required tool that utilizes a system-based computer. This medium can help officers part credit at RCB, to determine evaluation risk credit at RCB Tapin Sejahtera using the System Engineering Process (SEP) methodology, which requires a comprehensive design. The System Engineering Process (SEP) is an approach to the systematic development, operation, and maintenance of complex systems. The System Engineering Process (SEP) is a methodology that focuses on in-depth analysis, modeling, and testing throughout the development cycle to ensure the system meets user needs and functions optimally. The System Engineering Process (SEP) is well-suited to projects that require coordination among elements and ensure that the system meets the technical and operational needs. The methodology comprises several stages focused on understanding, designing, testing, and maintaining the system.

1. Requirements Analysis

The Requirements Analysis stage is an early and fundamental stage in the System Engineering Process (SEP) methodology, which aims to identify, analyze, and document the system evaluation risk and credit that will be developed. Stage This ensures that the system-based computer is designed in accordance with the technical and operational needs of RCB Tapin Sejahtera and capable of supporting the credit officer's optimal performance.

a. Business Process Identification Evaluation Outstanding Credit
   At this stage, this is done by mapping comprehensively to the assessment process and current credit. This is implemented at RCB Tapin Sejahtera. Activities covering the identification channel: Work officer credit starts with submission credit, debtor data collection, and eligibility analysis, and culminates in decision credit. Mapping this aim: to understand mechanism evaluation risks that still exist, manual or semi-manual, as well as identify potential weaknesses, limitations, and subjective errors in the process.
b. Identification Stakeholders Interests (Stakeholders)
   Stage: Identify all parties involved or affected by the system being built. Stakeholders' interests mainly cover the officer's role in the credit system, RCB management as the decision-maker, and the party's internal supervisor. Identification Isis essential to ensure that the stakeholders' needs and expectations of all can be accommodated proportionally in the system.
c. Analysis : Need User Requirements
   Analysis needs users to focus on the officer's needs in the operation task evaluation, risk, and credit. Needs this covering convenience in entering debtor data, an ability to process data quickly and consistently, and to present results, analysis, and risk in an easily understood format. The system can serve as a decision-support tool, reducing reliance on subjective judgment.
d. Formulation Need Functional System
   Need a functional formulation to describe the function, the main thing that the system must own. The need for this covering ability system to manage debtor data, conduct risk analysis based on determined criteria, present results as recommendations or risk categories, and support and report the credit assessment process. The formulation needs to be functional so that the system can support credit work processes comprehensively.
e. Formulation Non- Functional Requirements System

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Besides the need for functionality, the system must fulfill functional requirements that reflect the quality system. Non- functional requirements covering reliability and accuracy results assessment, convenience use for officer credit, debtor data security, and suitability system with infrastructure technology information held by RCB Tapin Sejahtera. It is essential to ensure the system operates safely and sustainably.

f. Analysis Technical and Operational Requirements
At this stage, this analysis requires technical systems, such as device hardware and software, and the necessary databases, as well as an operational integration system with the RCB work procedure that has been in place. Analysis: This ensures that the designed system can be implemented without bothering bank operations and in accordance with the available power source.

g. Documentation and Validation Need System
All over needs that have been identified Then documented in a way systematic in document need system (System Requirements Specification). Documentation This furthermore validated together stakeholders interests, in particular officer RCB credit and management, for ensure that formulated needs has in accordance with expectations and conditions real in the field. Validation This become base important before system enter to stage design (System Design).

2. System Design

The System Design Stage in the System Engineering Process (SEP) methodology aims to translate the system need formulated at the Requirements Analysis stage into a technical and architectural design. At this stage, this determined how the system evaluation risk credit-based computer will be built, integrated, and operated to support the performance officer RCB Tapin Sejahtera credit in general, effectively and efficiently.

a. Design Architecture System
Design architecture system done. To determine the overall system evaluation risk credit. An architecture system designed for an application computer, consisting of a number of components, namely: the user interface, the data processing module, the databases, and the analysis, risk, and credit module. Architecture: This is designed to support channel Work evaluation credit running at RCB Tapin Sejahtera, as well as to allow integration with the banking system that is there.

b. Module and Component Design System
At this stage, the solution is broken down into modules, each more functionally specific. Main modules designed include a debtor data input module, a credit data management module, a risk credit analysis module, and a results reporting and assessment module. Division module.. This aim is to facilitate the development, testing, and maintenance processes in a way that is coordinated but still flexible.

c. System Process Flow Design
The design system process flow describes how data flows from one module to another. The process flow begins with the data input by officers' credit, continues with validation and data processing, and culminates in the production of output in the form of a recommendation or a category risk credit. Design This ensures that every stage's evaluation credit is conducted systematically, consistently, and appropriately in accordance with the RCB operations procedure.

d. Database Design
Database design is done for thefor the support storage and management of debtor data, credit data, and risk analysis. The database structure is designed to be organized and integrated to ensure consistency, security, and convenient data access. Database design also takes into account the need for reporting and internal audit of RCB Tapin Sejahtera.

e. Design Interface User Interface
Interface users are designed with officers' convenience and patrol credit in mind. View system made simple, intuitive, and appropriate for daily operational needs, thereby reducing data input errors and improving work efficiency. Design interface. This aims to ensure the system can be used without technical skills or specialized knowledge.

f. Design Mechanism Analysis Risk Credit
At this stage, the designed mechanism analyzes the risk credit that the system will use. The mechanism covers determination criteria assessment, risk weighting factors, and method calculations that produce the risk level or category, and a credit mechanism design analysis customized with internal policies and principles, in line with the prudence of RCB Tapin Sejahtera.

g. Design Security and Control Access
Design a security system to protect debtor data and evaluate creditworthiness in the event of unauthorized access. The design includes the arrangement of the right access user, the authentication system, and user activity recording (logging). This is important for protecting data confidentiality and supporting internal supervision.

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h. Documentation Design System
The overall results design system is documented in the System Design Document. Documentation: This serves as the primary reference for stage implementation and testing, as well as for ensuring the development system is implemented consistently in accordance with the goals and needs set.

3. Implementation

Implementation Stage in System Engineering Process (SEP) methodology is stage realization from design the system that has been prepared at the System Design stage to in form system based computer that can used in a way operational stage This aim For ensure that all over component system evaluation risk credit can implemented in a way functional, integrated, and appropriate with need officer part RCB Tapin Sejahtera credit.

a. Preparation Environment Implementation
At the beginning of preparation, the environment implementation includes preparing the device hardware, device software, and the system's required infrastructure. Preparation: This is customized based on the condition technology information available at RCB Tapin Sejahtera, so the system can be executed optimally without the need to change significant infrastructure.

b. System Module Implementation
In every module, the system designed at the System Design stage is implemented step by step. The modules cover the debtor data input module, credit data management, risk credit analysis, and reporting results assessment. Implementation was done modularly to make testing and maintaining the system easier.

c. Database Implementation
At the stage This done database creation and configuration according to with the design that has been set . The database is used For storing debtor data , application data credit , as well as results analysis risk credit . Database implementation is carried out with notice consistency , security , and convenience data access for system .

d. Inter- Module Integration
After each module is implemented, the integration process is carried out across modules to ensure the system functions as a cohesive whole. The aim is to ensure that data flows correctly from the input process to produce an output in the form of a risk credit recommendation that credit officers can use.

e. Implementation Mechanism Analysis Risk Credit
At this stage, the implemented mechanism analyzes credit risk in accordance with the criteria and methods designed for it. Mechanism: This covers debtor data processing and calculations, and level risk credit in a systematic and consistent implementation . This aims to ensure that the system can produce an evaluation risk objective and acceptable credit support to support a credit decision.

f. Implementation Interface Users
Interface users implemented in accordance with designs, with a focus on officer convenience, part credit. View system made intuitive and straightforward to minimize input errors and increase efficiency. Work users in do evaluation risk credit.

g. Testing (Unit Testing)
Every module implemented has undergone testing to ensure that the function-based system meets the set requirements. Testing this aim: To detect and repair errors at the beginning of the stage, before the system is tested overall.

h. Documentation Implementation System
The entire implementation and configuration process is documented systematically. Documentation: This covers the instruction-use system, technical configuration, and notes on implementation, to be used as a reference at the stages of testing, continuation, implementation, and maintenance of the system.

4. Testing

Testing Stage in The System Engineering Process (SEP) methodology aims to ensure that the system evaluation risk developed credit has fulfilled the user's needs, functions in accordance with the design, and operates reliably in the RCB Tapin Sejahtera environment. Testing is conducted systematically to minimize errors and ensure accuracy, as well as to evaluate results and credit risk.

a. Planning Testing System
At this stage, the planned testing includes room scope testing, the methods used, test scenarios, and criteria for success. Planning is tailored to RCB Tapin Sejahtera's operations and refers to the needs, both functional and non-functional, identified during the Requirements Analysis stage.

b. Testing Functional Testing
Testing functionality ensures that every function system works as expected. Testing: This covers testing the debtor data input module, credit data management, risk credit analysis, and the module reporting. Every function is tested against the scenarios used by officers' credit to ensure it is suitable with RCB business processes.

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c. Integration Testing
After the module is tested separately, integration testing is performed to ensure that all modules can interact and exchange data correctly. Testing. The aim is to provide the assessment process flows correctly, from data input to the production of a risk credit recommendation, without errors or data inconsistencies.

d. System Performance Testing
Performance testing was conducted to evaluate the system's ability to process data and produce credit risk evaluation results in a reasonable time. Testing is essential to ensure that the system remains responsive and stable when officers use it daily in operational conditions.

e. Testing Security System (Security Testing)
Security testing must be conducted to ensure that the debtor data and results are protected from unauthorized access and are valid. Testing: This covers user authentication, controlling access rights, and protecting against data manipulation. Stage: This is important for protecting the confidentiality and integrity of banking data.

f. Testing Convenience Usability Testing
Testing convenience use is done with the officer's involvement in the user's system. Testing this aim: To evaluate whether the interface system is easy to understand, easy to use, and supports the efficient work of the credit officer, based on user input for improvement of the appearance and flow of the system.

g. Testing Reception User Acceptance Testing
Testing reception users is done to ensure that the system meets users' needs and expectations. At this stage, the officer, credit, and parties from RCB Tapin Sejahtera management evaluate the system as a whole before it is fully implemented. Test results. This becomes the base decision eligibility system for use.

h. Documentation and Evaluation of Test Results
Overall, results testing was documented systematically, including findings, errors, corrections made, and results evaluation. Documentation. This serves as a reference for the improvement system at this stage and supports maintenance and development processes for future systems.

5. Deployment

The Deployment Stage in the System Engineering Process (SEP) methodology is the stage of implementing system evaluation, risk, credit, and the operational stage of the computer-based environment for RCB Tapin Sejahtera. The aim is to ensure that the system, which has undergone design, implementation, and testing, can operate in a real, integrated way with ongoing business processes, as well as provide direct benefits to the officers' part credit.

a. Preparation Environment Operational
At this stage, the preparation of the environment and operational place system will be carried out. Preparation covering adjustment device hardware, device software, networks, and configuration system in accordance with the infrastructure technology information held by RCB Tapin Sejahtera. Stage: This aim is to ensure the system can walk in a stable, optimal way in the environment of bank operations.

b. Installation and Configuration System
System evaluation risk credit is installed in the prepared environmental operations. The installation process covers database settings, system parameter configuration, and the proper assignment of access rights to users. Configuration. This is done to ensure the system complies with internal policies and procedures for RCB Tapin Sejahtera's operational activities.

c. Integration with RCB Business Processes
At this stage, this system is integrated with channel work and business processes evaluation, which has been running at RCB Tapin Sejahtera. The integration aims to ensure that the use of system No bother operations that have been there is strengthened and supported, and to support the decision-making process more systematically and objectively.

d. Migration and Initial Data Entry
If necessary, perform the data migration from the system or from a previously recorded system. Initial data entry. This includes relevant debtor and credit data, so the system can be used directly in the risk credit assessment process without having to start from empty data.

e. Training and Socialization Users
Training and socialization are done for the officer part, as the user's central system. Activities: This aim is to provide an understanding of the method used in the system, the workflow, the interpretation of results, the evaluation of risk, and the credits generated by the system. Stage: This is important to ensure the system can be used most effectively, maximizing its use by the user.

f. Operational Test (Pilot Deployment)
System executed in a limited way during the operational test period, beginning. To ensure the system can function well in real conditions. At this stage, we have monitored the performance of the system and user responses to identify constraints or areas that require further adjustment.

g. Implementation Full System
After the system was stable and viable for use, the entire assessment process risk credit at RCB Tapin Sejahtera was implemented. System start was officially used as a tool to help officers determine evaluation risk credit.

h. Documentation and Handover Accept System
The entire deployment process is documented systematically, including guide usage, the configuration system, and operational procedures. Documentation. This becomes the base handover acceptance system for the RCB Tapin Sejahtera party and serves as a reference for stage maintenance and development.

6. Maintenance

Maintenance Stage in the System Engineering Process (SEP) methodology is a stage of maintenance and development, with sustainable system evaluation risk credit after the system is implemented in a way operational at RCB Tapin Sejahtera. Stage this aim. For the guard performance system to remain optimal, it must ensure it meets users' needs and adapts to changing operational conditions and banking policies.

a. System Performance Monitoring
At this stage, the monitoring performance system is disabled to ensure the system remains stable and consistent with the expected function. Monitoring covers speed data processing, reliability system, consistency results evaluation, and risk credit and monitoring results, which are used to identify potential disturbances or declines in system performance.

b. Maintenance Corrective
Maintenance corrective actions were taken to repair errors or disturbances found during system use. Activities: This covers bug fixes, errors, logic calculations, risk, credit, and module or database errors. Maintenance: This aims to ensure the system returns to regular operation and does not interfere with the assessment process.

c. Maintenance Preventive
Preventive maintenance measures are done to prevent future disturbances in future systems. Activities: This includes updating device software, checking database routines, performing data backups, and testing the security system against potential threats. Preventive maintenance measures aim to safeguard long-term stability and security.

d. Maintenance Adaptive
Maintenance adaptive done for the adapt system with change needs: BPR Tapin Sejahtera operations, policies, credit, or regulations in banking. Adjustments can be made through change criteria evaluation, risk credits, system parameter updates, or the addition of new features that support work processes and officer credit.

e. System Performance Evaluation and Improvement
At this stage, the evaluation is conducted periodically to assess performance and the system's benefits for officer part credit. Evaluation done with data gathered from users regarding the convenience of use, the accuracy of results, and the effectiveness of the system in supporting credit decisions. Evaluation results are used as a basis for the continued improvement and development of the system.

f. Data Management and Security
Maintaining the system also includes data management and security information. Activities: This covers management rights, user access, debtor data protection, and monitoring the activity system to prevent data misuse. This is important for the confidentiality of guards and the integrity of banking data.

g. Documentation and Reporting Maintenance
All over-activity maintenance is documented systematically, including the type of maintenance performed, the repairs applied, and the results evaluation system. Documentation. This serves as material reporting and provides technical and fundamental information to support decision-making for the development of future systems.

3.2. *Architecture System AIoT Evaluation Risk Credit*

Based on the Systems Engineering Process (SEP) methodology that you developed, as follows: is a design architecture AIoT that integrates agricultural data to in-system evaluation risk credit at the People's Credit Bank (RCB). Architecture: This is designed to transform physical data from land into objective financial insight.

Architecture System AIoT For Evaluation Risk Credit Agriculture. Architecture. This consists of four main layers that work continuously:

1. Perception Layer (Perception Layer) Perception / Land)
This is the point at which on-the-ground data collection for MSME agriculture begins.
AIoT Sensor: Uses a soil moisture (humidity) sensor, soil pH, environmental temperature, and light intensity.
Assets: Smart Camera for visually monitoring plant index, vegetation, or growth.
Field Data: Includes specific data representative of location risk production in a real way.

2. Network Layer (Layer) Network)

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A layer that ensures data from rural, remote areas reaches the banking system.
Protocol Communication: Using economical energy technologies like LoRaWAN (for range in rural areas) or cellular networks (4G/5G).
Edge Gateway: Performing initial data processing on-site to ensure only valid data is sent to the cloud.

3. Middleware & Processing Layer (Middleware Layer) AI Processing)
This is where the core of Systems Engineering comes into play. For processing non- financial data.
AI Analytics: Algorithmic intelligence artificial that processes weather data and conditions land to predict results for harvest (estimated capacity).
Synthesis: Combining physical data (AIoT) with traditional financial data (historical savings/credit at RCB).
Risk Engine: A machine that automatically calculates the risk score based on moderate agricultural parameters.

4. Application Layer (Layer) Applications at RCB)
The taker uses the final result to make decisions at RCB Tapin Sejahtera or other RCBs.
Analyst Dashboard Credit: Showing chart profile risk dynamic customers (up/ down) in accordance with the condition of the land.
Savvy Recommendation: The system provides automatic recommendations (Approve, Review Repeat, or Reject) based on the set risk threshold.
Early Warning System: Automatic notification to the bank if the sensor detects anomalies (such as extreme drought) that could lead to future payment failures.

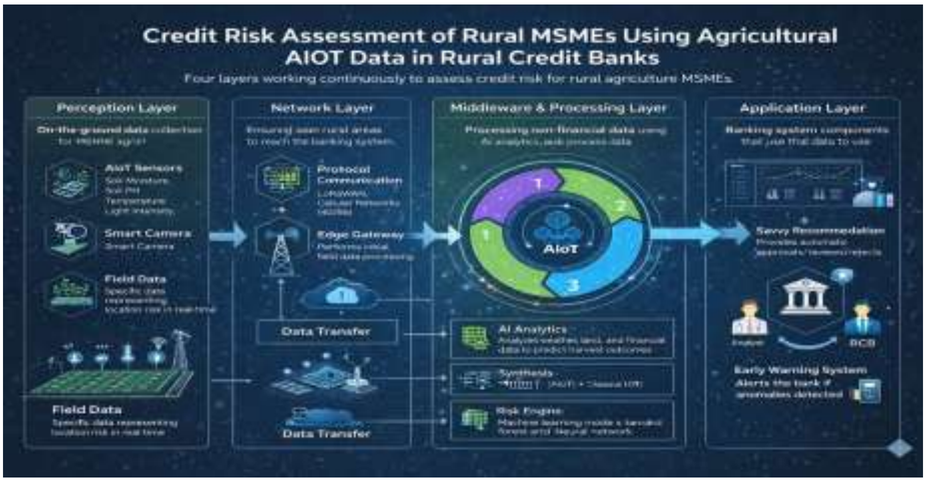

Figure 3. Architecture System AIoT Evaluation Risk Credit

4. Conclusion

This concludes that implementing *the Systems Engineering Process* (SEP) is a practical, systematic approach for developing a system evaluation risk framework in the MSME credit sector in agriculture at the People's Credit Bank (RCB), as it can integrate technical and operational needs comprehensively. Through structured SEP stages, agricultural data can be transformed from raw data into relevant and valuable information, supporting decision-making with greater credibility, objectivity, and accuracy. Real-time, contextual integration of non-financial data complements financial data evaluation using conventional methods, reducing subjectivity, increasing risk evaluation accuracy, and strengthening inclusion in finance for rural MSMEs. This approach also ensures a system that is adaptive, sustainable, and feasible, implemented as a development model, with system evaluation, risk, and credit to the institutions sector, focused on finance and agriculture.

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