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Integration of AI Models and Extreme Programming for Retail Price Prediction and Inventory Optimization

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ABSTRACT

Food prices in modern retail are highly volatile and complex inventory management is often an obstacle to maintaining operational efficiency. The research developed Smart Retail AI, an artificial intelligence-based application that integrates Long Short-Term Memory (LSTM) for price prediction and Extreme Gradient Boosting (XGBoost) for stock optimization. The software development method uses the Agile Extreme Programming (XP) approach, which emphasizes rapid iteration, user engagement, and continuous testing. The test results showed that all application features worked according to the specifications through Black Box Testing, while the usability test using the System Usability Scale (SUS) resulted in an average score of 87 (Excellent category). These findings confirm that the app has high reliability and an excellent level of ease of use. The novelty of the research lies in the direct integration of AI-based predictive models into real operational retail applications with the XP cycle, thus bridging the gap between algorithmic research and practical application. Overall, Smart Retail AI contributes to improving decision-making efficiency, operational responsiveness, and business sustainability in the modern retail ecosystem.

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1. INTRODUCTION

The rapid transformation in retail business models in the digital age has demanded profound changes in consumer behavior as well as in supply chain management strategies [1-3]. Modern retail, which relies on digital platform integration, real-time data analytics, and decision-making automation, needs systems that can provide accurate predictive information to maintain operational efficiency and maintain a competitive advantage [4-6]. On the other hand, the food sector is facing high challenges due to extreme commodity price volatility and complex inventory management. Price fluctuations are triggered by seasonal conditions, disruptions in supply chains, and sudden changes in demand patterns, resulting in difficulties in setting optimal stock levels without disrupting profit margins [7], [8]. This situation indicates the need for the application of artificial intelligence-based technology, which has the potential to support faster and more precise decision-making.

Artificial intelligence (AI) is increasingly recognized as a strategic solution to prediction and optimization challenges, including in the retail realm [9], [10]. Machine learning methods, such as Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost), have shown high

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performance in time series forecasting and predictive analytics in research contexts [11]. Nonetheless, some of the research has tended to focus on model development and evaluation of accuracy in offline scenarios, ignoring the move to the integration stage into an operational and ready-to-use application system in a real-world context.

Previous research has provided an important foundation for this study. The Long Short-Term Memory (LSTM) model shows superior ability to predict e-grocery demand compared to traditional methods, but it has not yet been integrated into daily operations. Decision tree-based methods such as XGBoost show excellent performance when tested on physical retail data, but they do not yet have an end-user accessible interface. The combination of LSTM and LightGBM, accompanied by pre-processing techniques, does result in higher precision, but all of that exploration is boxed into a simulated environment. Some studies compare standard-models with hybrid models such as Random Forest, XGBoost, and Linear Regression; Despite the high accuracy, the relationship between the findings and real use in retail applications has not been established. Finally, studies of the Extreme Programming (XP) methodology have shown a positive impact on improving software quality through rapid development cycles and continuous testing, but the application of this methodology to the development of AI-based systems in contemporary retail is still minimal.

From the overall review above, it can be seen that the gaps that need to be filled in further research:

a. the development of AI models remains separate from integration in the operational environment,
b. the application of the XP methodology to AI-based retail systems has not been expanded, and
c. the evaluation of the system is holistic, measuring the accuracy of predictions, system performance, and user satisfaction levels in a single research frame, almost unfounded.

To answer this gap, this study proposes the development of price prediction and food stock optimization applications for modern retail, utilizing artificial intelligence and Agile software development methods based on Extreme Programming. The designed application will integrate AI-based prediction models into a ready-to-operate system, through responsive development cycles, rapid prototyping, continuous testing, and active user participation at every stage. With this approach, this study aims to strengthen the application of artificial intelligence in modern retail, while improving operational efficiency, competitiveness, and corporate sustainability.

2. RESEARCH METHOD

This study uses the Extreme Programming (XP) method, which is one of the approaches in the framework of Agile Software Development. The choice of the XP method is based on its characteristics that are able to speed up the development process through short iterations, active user engagement, rapid prototyping, and continuous testing. This approach is particularly suitable for the development of applications that require accurate predictions based on artificial intelligence as well as adaptability to changing user needs in the modern retail sector. This research stage is designed to ensure that the process runs systematically, starting from problem identification to evaluation of implementation results. In general, the stages of research include:

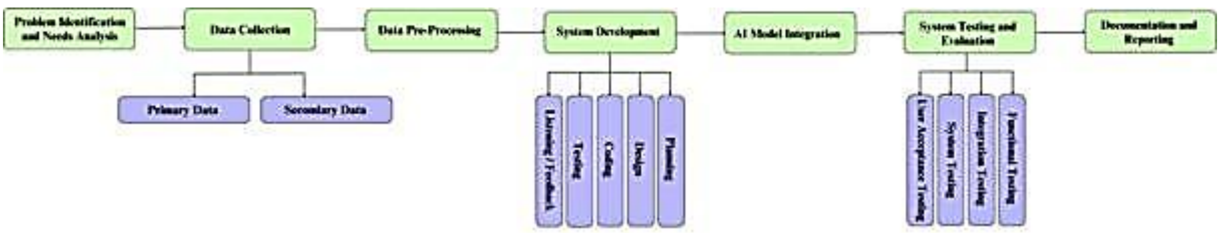

Figure 1. Research Methodology

2.1. Problem Identification and Needs Analysis

This initial stage aims to understand the problems faced by modern retailers, especially related to food price fluctuations and stock management. The identification process is carried out through literature studies, interviews with stakeholders, and analysis of ongoing business processes. The resulthis is how

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to start a subsection of this stage is a list of core problems and opportunities for the development of artificial intelligence- based systems.

2.2. Data Collection

Data collection techniques include interviews and documentation, so that the information obtained includes both practical perspectives from the field and measured historical data. The data used consisted of:

1. Primary data: collected through in-depth interviews with retail managers, warehouse managers, and operational staff to obtain information about system requirements, stock workflows, and pricing policies.
2. Secondary data: obtained from historical sales documents, inventory records, price fluctuation reports, as well as scientific literature and online sources relevant to the study.

2.3. Pre-Processing Data

The data that has been collected is processed through the stages of data cleaning, normalization, and feature encoding. At this stage, datasets are also shared for AI model training and testing.

2.4. System Development

Application development is carried out using the Agile Software Development method using the Extreme Programming (XP) approach. This approach was chosen because it is able to accommodate rapidly changing user needs, facilitate iterative prototyping, and implement continuous testing.

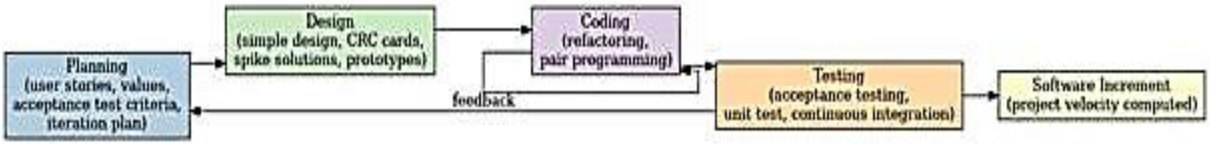

Figure 2. Extreme Programming

The XP stages applied include [19]:

1. Planning, identifying user stories, feature priorities, and iteration targets.
2. Design, designing system architecture and user interface.
3. Coding, code implementation with pair programming and code review.
4. Testing, unit testing, integration, and performance of AI models in each iteration.
5. Listening/Feedback, evaluation with users for feature improvements.

2.5. AI Model Integration

The artificial intelligence model used combines Long Short-Term Memory (LSTM) algorithms for price forecasting and Extreme Gradient Boosting (XGBoost) for price factor analysis as well as stock optimization. The trained model is integrated into the application backend so that it can be accessed in real-time by the user.

2.6. System Testing and Evaluation

Testing is carried out to ensure that the application developed is in accordance with the needs and specifications that have been set at the planning stage. Testing focuses on aspects of software development, which include:

1. Functional Testing – ensuring that each app's feature works according to the agreed user stories.
2. Integration Testing – verifies that all system components, including the user interface, backend, and database, are connected to each other and work without errors.
3. System Testing – evaluates the overall performance of an application in a usage scenario that resembles real conditions in a modern retail environment.

User Acceptance Testing (UAT) – involves the end user to ensure that the application meets expectations and can be used effectively in day-to-day operations.

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2.7. Documentation and Reporting

The final stage is the preparation of technical documentation and research reports, which include analysis of results, discussion of contributions, and recommendations for further development.

3. RESULTS AND DISCUSSION

This section presents the results of the development of artificial intelligence-based applications for price prediction and optimization of modern retail food stocks. The methodology used is Agile Software Development with an Extreme Programming (XP) approach. This approach was chosen for its ability to respond quickly to changing user needs, maintain software quality through continuous testing, and accelerate release cycles with short iterations. The development stages follow the main cycle of XP: planning, design, coding, and testing with stakeholders directly involved in each step. The finish not only meets functional specifications, but also demonstrates a high level of usability in the context of modern retail operations.

3.1 Planing

The planning stage is focused on identifying system needs through the creation of user stories from the perspective of the Operational Manager, Procurement/Purchasing Team, and Warehouse Manager. The activity was carried out through interviews and discussions with stakeholders to explore the workflow, problems faced, as well as priority features such as AI-based food price prediction, automated stock optimization, purchase request management, supplier data management, and critical stock notifications. In addition, acceptance test criteria are prepared as a reference for feature acceptance and an iteration plan that divides development into weekly cycles. The result of this stage is a planning document containing a list of user stories, development priorities, iteration schedules, and acceptance criteria for each feature.

3.2 Design

At this stage, a use case diagram was designed to map the interaction between actors and system features, an activity diagram was created to describe the main process flow, a database table was compiled to support data management, and wireframe was created as an initial prototype of the user interface. This design ensures that all system components are well-structured and aligned with the user's needs. Figure 3 is a use case diagram that illustrates the relationship between the main actors and the system functions.

Figure 3. Use Case Diagram Operation Manager

Figure 3 is a use case diagram that shows the interaction between Operations Manager and the system. These actors have a critical role in monitoring and controlling retail operations, from the login process to strategic decision management. Accessible functions include viewing a stock and price summary dashboard, monitoring AI-based price predictions, viewing estimated needs per branch, setting target stock levels (minimum, maximum, and safety stock), and approving an automatic restocking plan. In addition, Operations Manager can set notification policies (e.g. critical stock or overstock), monitor distribution status and delivery times, plan distributions between branches, and generate reports in various formats such as PDF or CSV for further analysis. The next use case diagram is Procurement / Purchasing Team.

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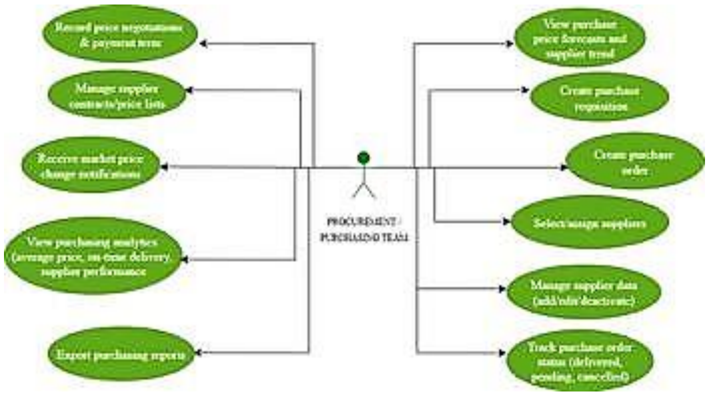

Figure 4. Use Case Diagram Procurement

The use case diagram above illustrates the role of the Procurement/Purchasing Team in managing the entire purchasing process, starting from looking at purchase price predictions and supplier trends, making purchase requisition and purchase orders, selecting and assigning suppliers, to managing supplier data. This team is also tasked with tracking the status of purchase orders (delivered, pending, cancelled), recording price negotiations and payment terms, managing contracts or supplier price lists, and receiving notifications of market price changes. Additionally, teams can view purchasing analytics such as average prices, delivery timeliness, and supplier performance, as well as export purchase reports for evaluation.

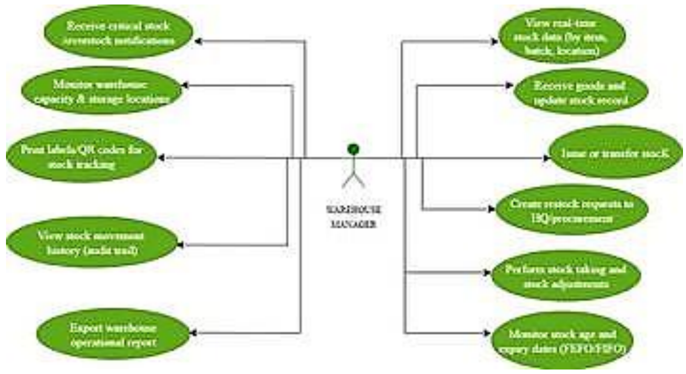

Figure 5. Use Case Procurement

The Warehouse Manager use case diagram shows all the key interactions for managing physical stock in the warehouse: from viewing real-time stock data (by item, batch, location), receiving goods and updating stock records, to issuing or transferring stock as per operational needs. This role can also make restock requests to the center/procurement, conduct stock taking and stock adjustments, and monitor stock age and expiration date (FEFO/FIFO) to prevent stockouts and accumulation of expired goods. To maintain efficiency, the Warehouse Manager monitors warehouse capacity and storage locations, receives critical stock notifications/overstock, prints labels/QR for tracking, reviews stock movement history (audit trail), and exports operational reports. Next, an activity diagram will be displayed.

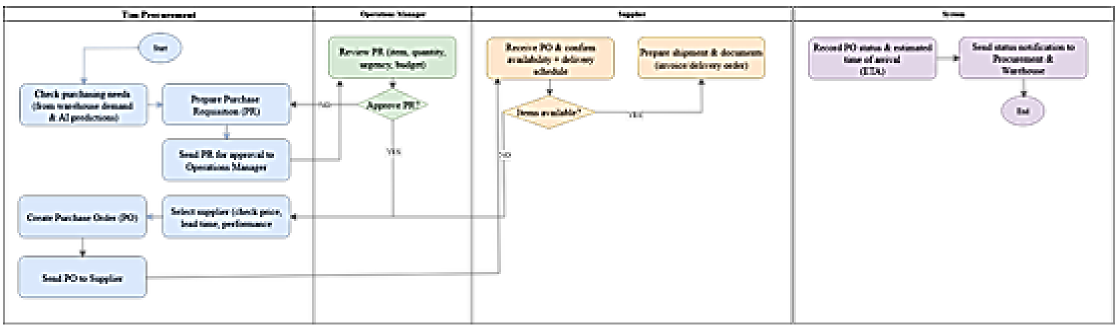

Figure 6. Activity Diagram of the Purchasing Process

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Figure 6 above shows the activity diagram of the goods purchase process involving four swimlanes, namely the Procurement Team, Operations Manager, Supplier, and System. This diagram illustrates the flow from checking purchase needs to sending order status notifications to Procurement and Warehouse. Next, an activity diagram of the Goods Purchase Process will be displayed.

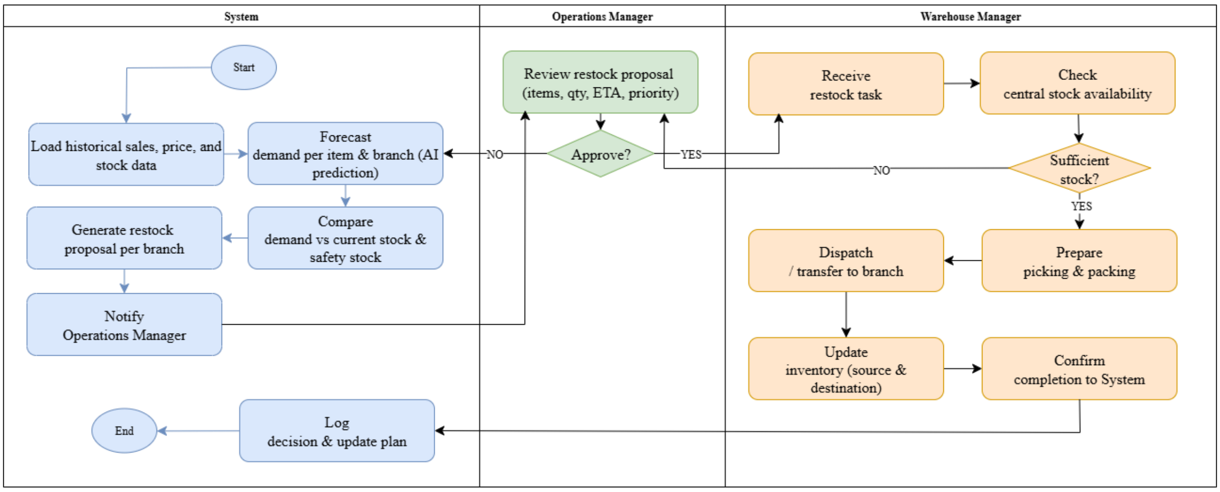

Figure 7. Activity diagram of the automatic restocking process

Figure 7 above is an activity diagram of the Automatic Restocking process involving three main swimlanes, namely System/AI, Operations Manager, and Warehouse Manager. This diagram shows the flow from the processing of historical data by the system, the creation of demand predictions, the approval of the restocking plan by the Operations Manager, to the execution of stock distribution by the Warehouse Manager and the update of the inventory record.

Figure 8. Wireframe System

3.3 Coding

The coding stage in the Extreme Programming (XP) method focuses on translating the system design into program code that works according to the needs of the user. The implementation is carried out with the principle of pair programming to improve the quality and accuracy of the code, as well as the practice of continuous integration so that every change can be tested immediately. Artificial intelligence models for price prediction and stock optimization are integrated into the application backend at this stage, while the refactoring process is ongoing to ensure the code structure remains efficient, easy to maintain, and ready for the testing phase.

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Figure 9. Login Page

The login page serves as an initial authentication gateway before the user accesses system features, ensuring secure access and proper role mapping. The interface is designed to be compact with the main elements in the form of Email/Username and Password fields, Login buttons, Forgot Password links, and List options (if allowed). Client-side and server-side validation are applied for email formats, password lengths, and clear error feedback; meanwhile, a "Remember me" mechanism and rate limiting/captcha (optional) are set up to improve the experience and security. Next the home page will be displayed in Figure 10.

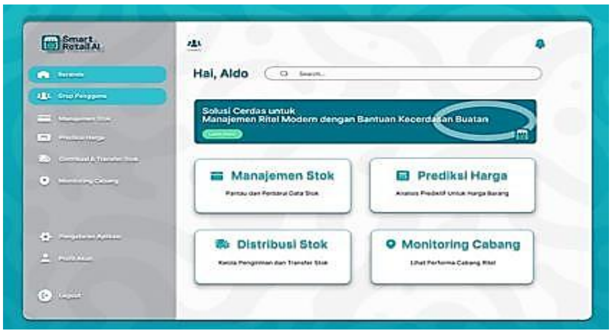

Figure 10. Warehouse Manager Page

Figure 10 presents the Warehouse Manager interface in the mobile edition of the Smart Retail AI app, which is optimized for inventory management and goods receipt management. In this interface, essential components, including Stock Data, Goods Receipts, Daily Sales, and Statistics, are organized in bottom navigation tabs for easy access to the menu. Warehouse managers are also given access to check daily stock demands, so that they can monitor the details of the quantity and type of goods requested and also record the receipt of goods with regular and documented historical records. In addition, warehouse management has other pages, including Home (Dashboard), Stock Data, Receipt of Goods, Expenses or Stock Transfers, and Notifications. Next, the Data Analyst page will be presented.

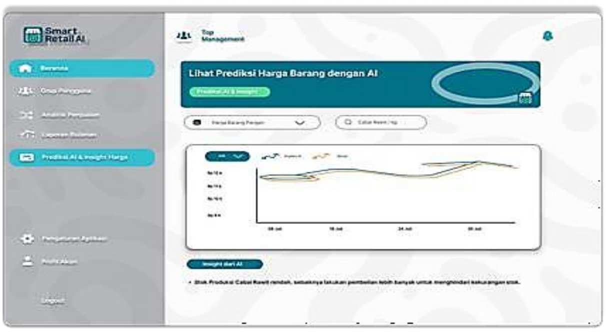

Figure 11. Warehouse Manager Page

Figure 12 presents the Warehouse Manager interface in the mobile edition of the Smart Retail AI app, which is optimized for inventory management and goods receipt management. In this interface, essential components, including Stock Data, Goods Receipts, Daily Sales, and Statistics, are organized in bottom navigation tabs for easy access to the menu. Warehouse managers are also given access to

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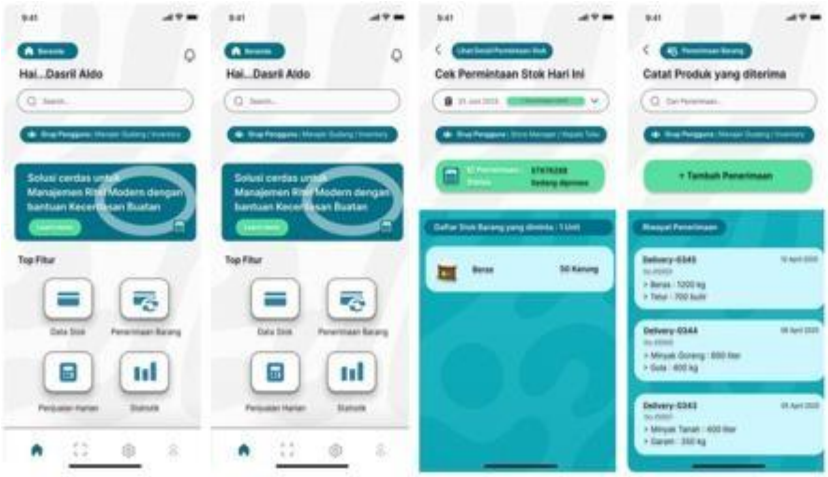

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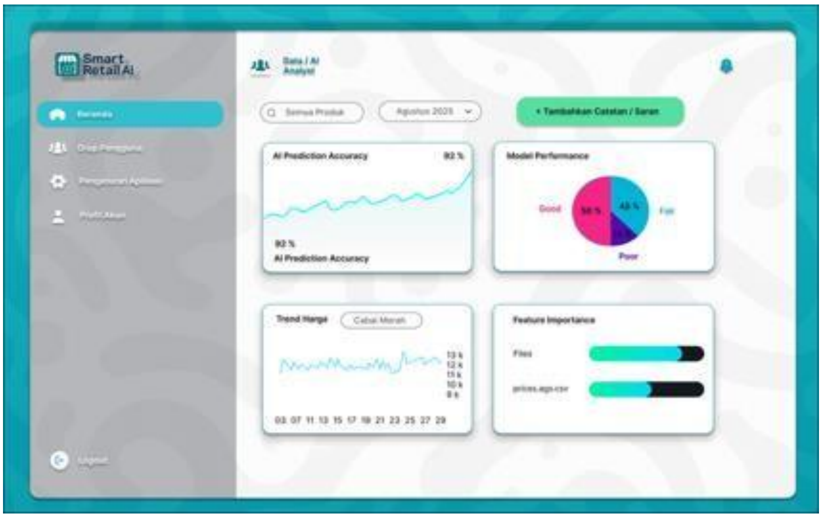

Figure 13. Data Analyst Page

Figure 13 shows the Dashboard & Main Menu page view for the Data Analyst/ AI Specialist role in the Smart Retail AI application. This interface displays the performance substance of the artificial intelligence model, starting from the predictive accuracy value, the distribution of the model performance categories differentiated into Good, Fair, and Poor labels, to the analysis of price trends for a specific product, in this example red chili. In addition, this page includes a feature importance graph that outlines the relative contribution of each variable to the final prediction, along with the option to insert notes and recommendations. The combination of these functions supports Data Analysts and AI Specialists in continuously monitoring, analyzing, and adjusting models to maintain the accuracy and

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relevance of predictions. In addition to these roles, this interface is also intended for Operations Managers, Procurement Teams, Inventory Controllers, Data Analysts, Store Managers, and Top Management.

3.4 Testing

Testing in the Extreme Programming (XP) methodology is designed to guarantee that each feature released operates according to user expectations and meets the quality criteria that have been formulated. Test activities run on a recurring basis after the completion of each development iteration, so that any anomalies can be identified and corrected immediately. The method adopted is Black Box Testing, where attention is paid to the behavior of the system without conducting an inspection of the source code. Each feature is evaluated through a series of scenarios that assume a wide range of inputs, and the output obtained is compared to the results that have been formulated in the specification. In this way, the system is explored in a wide range of situations including legitimate inputs, condition-violating inputs, and exact scenarios being at the limits of specifications that collectively demonstrate that the developed functions are capable of meeting the needs of the user consistently.

Table 1. Blackbox Testing

ID	Feature	Test Case	Precondition	Expected Output	Status
TC-01	Authentication	Login with valid credentials	username=valid, password=valid	Redirect to dashboard; session created	Success
TC-02	Authentication	Login with invalid password	username=valid, password=wrong	Error message shown; stay on login page	Success
TC-21	Notifications	Overstock alert	stock >= max level	Overstock notification displayed	Success
…..	…..	…..	…..	…..	…..
TC-23	Reports	Export without permission	user lacks role	Access denied message	Success

Black box testing of the Smart Retail AI application demonstrated that every function, from authentication to the final report generation phase, operated without deviation from the specified specifications. This finding indicates that the platform has achieved the level of reliability required for application in a contemporary retail context. Following this verification phase, the testing team then conducted an evaluation using the System Usability Scale (SUS) metrics to measure the system's usability dimensions.

Table 2. System Usability Scale (SUS) Testing

Respond	1	2	3	4	5	6	7	8	9	10	Sum	Value (Total x 2.5)
R1	5	2	5	2	4	2	5	2	5	1	35	87,5
R2	5	1	5	2	5	2	5	1	5	2	34	85
R3	5	2	5	2	5	2	4	2	5	2	34	85
R4	5	1	5	1	5	1	5	1	5	1	37	92,5
R5	4	2	5	2	5	2	5	2	5	1	34	85
R6	5	1	5	2	4	1	5	1	5	1	35	87,5
R7	5	1	5	1	5	1	5	1	5	1	37	92,5
R8	5	1	5	1	5	2	5	1	5	2	36	90
R9	4	2	4	2	5	2	5	2	5	2	33	82,5
R10	5	1	5	1	5	1	5	1	5	1	37	92,5
R11	5	2	5	2	5	2	5	2	5	1	35	87,5
Total number of scores												**957**
Avarage												**87**

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Based on the analysis of the System Usability Scale (SUS) score shown in the table above, an average score of 87 was obtained, which in reference to the SUS standard is in the Excellent category. This score indicates that Smart Retail AI applications have a very high level of usability, adequate ease of use, and features that users consider relevant. Given that this value is well above its category threshold, which is 68 (Good category), it can be concluded that the application is feasible to implement and has the potential to be positively received by users in the modern retail operational environment.

The listening/feedback process in the development of the Smart Retail AI application is carried out after the initial release of the application in a staging environment and is used by users who act as Operations Managers, Procurement Team members, and Warehouse Managers. In this phase, users run all features related to their respective tasks, starting from logging in, accessing the dashboard, reviewing price predictions, compiling purchase requests, processing restocking, to recording the receipt of goods. Feedback was obtained through brief interviews, integrated online forms, and hands-on observation by the developer team. Analysis of this feedback led to several suggestions for improvement, including clarification of navigation menu labels, the addition of status indicators to the restocking process, and an increase in the loading speed of price prediction pages. All of these inputs are thoroughly vetted and implemented in subsequent iterations of development, with the goal of ensuring that the application is referenced, functions optimally, and is in line with operational needs in the field.

4. CONCLUSION

This research successfully developed Smart Retail AI, an application that integrates artificial intelligence for price prediction and food stock optimization in modern retail chains. Development was conducted using an Agile Software Development approach using the Extreme Programming (XP) method. All phases of planning, design, coding, testing, and feedback were executed iteratively, involving three key stakeholders: the Operations Manager, the Procurement Team, and the Warehouse Manager. Black Box testing results showed that all core modules and key features, including user authentication, the dashboard, AI-based price prediction, automatic restocking, procurement management, stock receiving and distribution, and operational reports, performed according to specifications. Evaluation using the System Usability Scale (SUS) yielded an average score of 87, which falls within the Excellent category. This indicates that the application not only functions well but also has a high level of usability.

Furthermore, the listening and feedback phase provided important input, including improvements to navigation menu labels, the addition of status indicators for the restocking process, and optimization of load times in the price prediction module. This feedback was integrated into subsequent development iterations to improve the application's responsiveness, clarity, and suitability to operational needs. From a scientific perspective, this research contributes by integrating AI-based predictive models (LSTM and XGBoost) into a real-world retail system using the XP cycle, thus bridging the gap between algorithmic research previously limited to simulation and operational implementation. This contribution strengthens the understanding of how AI can be effectively operationalized in modern retail supply chain management, while providing a foundation for further research to explore the evaluation of prediction metrics (RMSE, MAE, MAPE), comparison with baseline models, and generalization to broader data scales and populations. Thus, Smart Retail AI is not only ready to be implemented as a practical tool that supports fast, accurate, and efficient decision-making, but also provides an academic contribution in the form of an AI integration framework and XP methods that can be used as a reference in research and implementation of intelligent systems in retail and similar domains.

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