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Research Article

Development of Work Program Submission System Using Predictive Data Analytics Based on Neural Network Algorithms at PT Pos Lhokseumawe

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A B S T R A C T

The digital transformation within PT. Pos Indonesia KC Lhokseumawe demands a more efficient, secure, and adaptive procurement system. This study aims to develop a web-based work program submission system that integrates predictive analytics and neural network algorithms to enhance procurement efficiency and the accuracy of budget forecasting. The system is built using a React.js-based frontend architecture and a FastAPI-based backend, with MongoDB as the database. The N-BEATS model is implemented for time series-based budget forecasting, while Neural Collaborative Filtering is employed to recommend vendors based on interaction history. Evaluation results demonstrate strong performance, with an R-squared value of 0.9965 for the forecasting model and an F1-score of 73.71% for the recommendation model. This integrated system provides procurement management features, budget forecasting, and tender recommendations, and is expected to improve business process efficiency at PT significantly.

1. INTRODUCTION

PT Pos Indonesia is a company engaged in logistics courier and financial services. The company is preparing to undergo a transformation and build competencies as an adaptive organization in the face of ongoing advancements. The Industrial Revolution 4.0 has driven PT Pos Indonesia to consistently pursue digital transformation to deliver excellent services to all stakeholders. Information technology plays a powerful role in industry development and system transformation. To support this digital transformation, PT Pos Indonesia is striving to complete its information technology infrastructure through various goods/services procurement activities for each division under the IT Directorate [1].

Procurement is the process of obtaining goods or services, either under contract or through direct purchase, to meet business needs [2]. At PT Pos Indonesia, procurement is handled by the IT Strategy and Governance division. Currently, the procurement process is still conducted conventionally and has not yet been digitized. This results in a lack of security for important documents such as the Terms of Reference (TOR), Engineer's Estimate (EE), and Technical Study. The absence of security measures for these documents poses various risks, such as the potential loss of files. The rapid revolution in science and technology, along with the emergence of technologies like the Internet of Things, wireless sensor networks, cloud computing, and artificial intelligence, has ushered in the era of Big Data. Large volumes of data can yield more accurate information [3]. The application of machine learning can further assist in making predictions. These findings contribute to the literature and provide recommendations for future development [4]. To address these challenges, the author proposes developing a web-based system to improve efficiency and security in the procurement process. The website is designed to streamline IT procurement activities within the company and safeguard important procurement documents [5].

A study by Ratna et al. (2021) analyzed the parameters that help buyers select Vespa spare parts. The Content-Based Filtering (CBF) method, using the TF-IDF algorithm, was adopted as a search algorithm to analyze buyer needs and recommend vendors that classify products based on buyer criteria. CBF requires item or user profile descriptions that match the selected criteria to generate recommendations [6]. Another study by Triana et al. (2019) used CBF in a search application that compares user-viewed item classifications with those of other items in the system. This approach proved effective in recommending products with similar classifications. However, it does not yet support scenarios in which classifications are selected directly by users, rather than inferred from viewing behavior.

Based on the background described above, the author intends to design a system to digitize the procurement process at PT Pos Indonesia by creating a web-based procurement submission application and developing a predictive data analytics system [7]. This system aims to simplify procurement submissions for PT Pos Indonesia and vendors participating in procurement tenders. Additionally, the system will include a budget forecasting feature to help predict the company's expenses during the procurement process.

2. METHOD

This study adopts an experimental quantitative approach that combines machine learning-based predictive modeling with the development of a web-based information system. This approach aims not only to build a technically functional system but also to empirically measure its effectiveness in procuring goods and services [4].

2.1. Data Analysis and Processing

The training data was sourced from Kaggle, specifically the Singapore government procurement dataset, which includes key information such as award date, contract value, vendor name, and project description. This dataset has a structure similar to public procurement systems, making it relevant for building and validating predictive models.

In addition, for the recommendation model, the Movie Lens 100k dataset was used as a proxy for user-vendor interaction data. This dataset provides a user-item interaction scenario that can be modeled as implicit feedback, reflecting whether vendors participate in tenders within the developed system. Although this serves as a form of simulation, the interaction structure it offers is highly valuable for the initial testing of the Neural Collaborative Filtering (NCF) model and for scientific reference related to time series modeling using deep learning, particularly N-BEATS, as well as collaborative filtering with a neural network approach [8]. References were obtained from scientific journals, books, white papers, and documentation for machine learning frameworks, including PyTorch. This stage includes preprocessing historical procurement data, such as converting dates to a time-series format, normalizing budget values, and grouping data by category and time period. The next step involves training a forecasting model using the N-BEATS architecture to predict future procurement costs based on historical patterns. For the recommendation engine, a neural network-based collaborative filtering method was used, trained on vendor interaction data from previous tenders. The model recommends tenders to vendors based on historical compatibility and patterns learned from interaction logs [9].

2.2. System Design

This study designs a web-based system to support the procurement of goods and services by integrating machine learning models [10]. The initial phase focuses on preparing time-series data and vendor-tender interactions, including data cleaning, date conversion, aggregation, normalization, encoding, and data splitting and batch creation for model training [11]. The system is built using a ReactJS frontend and a FastAPI backend, with two main models: N-BEATS for accurate and efficient procurement cost forecasting and Neural Collaborative Filtering (NCF) for tender recommendation based on vendor interaction history [12]. The models are trained separately using PyTorch and then integrated into the system. The inference results from the models are delivered via REST API to the admin dashboard and vendor tender recommendation pages. NGINX is used as a reverse proxy and traffic manager. Main features of the system: Real-time visualization of procurement cost predictions, tender list display with vendor recommendation scores, interactive web interface for admin and vendor users [9].

2.3. System Evaluation

System evaluation is carried out in two stages: machine learning model evaluation and system integration evaluation. Model evaluation involves *Forecasting:* MAE, RMSE, R^2, and *Recommendation:* Hit Rate, MRR, Precision, Recall, F1-score, and Accuracy [13]. System integration evaluation is conducted by observing visual outputs and system responsiveness through the user interface, as well as testing API performance.
Final result: The system is proven to deliver highly accurate budget predictions and relevant tender recommendations. The integration performance is stable and responsive, and the system is ready for further development, including internal data integration and progress toward a hybrid recommender model. This system provides real added value in enhancing procurement efficiency at PT Pos Indonesia. This study was conducted at PT. Pos Indonesia, Lhokseumawe Branch Office, located in Lhokseumawe, Aceh Province, oversees 26 sub-branch offices across 5 regencies/cities.

The following is the procurement recording workflow currently implemented at PT. Pos Indonesia in Figure 1.

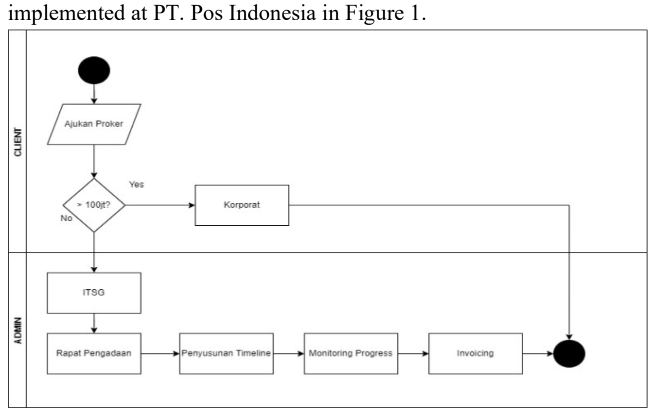

Figure1. Current System Analysis

Figure 1. Illustrates the current workflow for recording goods/services procurement at PT. Pos Indonesia. Procurement is initiated by the client and reviewed based on the client's budget. If the value exceeds 100 million, it is handled by the corporate office, while ITSG manages procurement below 100 million. ITSG then conducts a meeting to determine the procurement method, timeline, and partners. The procurement progress is recorded in an Excel/Spreadsheet and shared with the procurement owner for monitoring purposes.

The system requirements analysis for the Smart Procurement application is conducted to ensure the effectiveness of the functionalities and the integration of AI technology to support the procurement process. This analysis is divided into two main aspects: User Requirements and System and Technical Requirements. The User Requirements are intended for internal users such as procurement admins and budget managers. Meanwhile, the System and Technical Requirements specify a system built on a full-stack architecture with machine learning integration. This analysis serves as the foundation for system design and the development of prediction- and recommendation-based features to enhance the company's procurement efficiency [4]. The following is the system design used in developing the forecasting and collaborative filtering models shown in Figure 2.

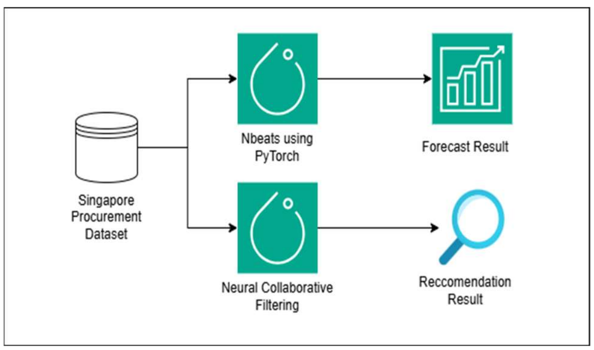

Figure 2. System Design

This section explains the system design for developing forecasting and collaborative filtering models. The system is divided into two main processes: a forecasting model that predicts trends based on historical data, and collaborative filtering that recommends items or vendors based on user interactions. Although both models use the same dataset, they apply different algorithmic approaches suited to their respective purposes, as shown in Figure 3.

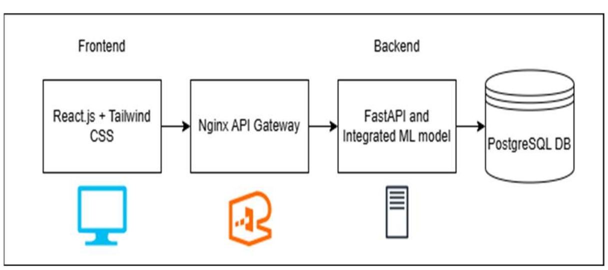

Figure 3. System Architecture

The system architecture uses ReactJS and Tailwind CSS on the frontend to provide a responsive interface. Requests from the frontend are routed through Nginx as an API Gateway, which handles routing, security, and load balancing. The backend is integrated with machine learning models to enable real-time prediction and recommendation. Data is stored in PostgreSQL [14], chosen for its scalability and consistency in managing transaction and user interaction data. This combination of technologies results in a system that is efficient, modular, and easy to develop further [4]. The data processing, analysis, and model development consist of a forecasting model and Neural Collaborative Filtering (NCF).

2.4. *Forecasting*

Data processing focuses on two main columns: *award_date* and *awarded_amt*. The data is cleaned of invalid entries, then converted and grouped by year for time-series analysis. The model is trained on historical data with future targets, with data split into batches to enable more efficient training. The model learns patterns over a specific time range to predict the next period [15].

```python
import pandas as pd
import numpy as np

# load the dataset
df = pd.read_csv('government-procurement-via-gebiz.csv')

# parse dates
df['award_date'] = pd.to_datetime(df['award_date'], errors='coerce')

# drop rows with invalid dates or missing award values
df = df.dropna(subset=['award_date', 'awarded_amt'])

# make sure awarded_amt is numeric (in case it has strings or weird symbols)
df['awarded_amt'] = pd.to_numeric(df['awarded_amt'], errors='coerce')
df = df.dropna(subset=['awarded_amt'])

# group by month
df_monthly = df.groupby(df['award_date'].dt.to_period('M'))['awarded_amt'].sum().reset_index()

# convert Period to datetime (for plotting and numpy)
df_monthly['award_date'] = df_monthly['award_date'].dt.to_timestamp()

# sort just to be sure
df_monthly = df_monthly.sort_values('award_date')

# extract x and y
x = df_monthly['award_date'].to_numpy()
y = df_monthly['awarded_amt'].to_numpy()
```

Figure 4. Forecasting Process

```python
from nbeats_pytorch.model import NBeatsNet

# Step 3: Define and Train the N-BEATS Model
device = 'cuda' if torch.cuda.is_available() else 'cpu'

# Define N-BEATS model
model = NBeatsNet(
    device=device,
    stack_types=(NBeatsNet.GENERIC_BLOCK, NBeatsNet.GENERIC_BLOCK),
    forecast_length=forecast_length,
    backcast_length=backcast_length,
    hidden_layer_units=128
).to(device)

# Define loss and optimizer
criterion = torch.nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters())

# Training loop
epochs = 50

for epoch in range(epochs):
    for x_batch, y_batch in dataloader:
        x_batch, y_batch = x_batch.to(device), y_batch.to(device)
        optimizer.zero_grad()
        backcast, forecast = model(x_batch)
        loss = criterion(forecast, y_batch)
        loss.backward()
        optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f'Epoch {epoch + 1}/{epochs}, Loss: {loss.item()}')
```

Figure 5. Data Time Series Process

2.5. *Neural Collaborative Filtering (NCF)*

The NCF model is used to recommend items based on users' interaction history. It uses embeddings to represent users and items as low-dimensional vectors [16]. Interaction data is cleaned, converted into binary format, and mapped to numerical indices. The data is processed in batches

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using a PyTorch DataLoader and trained with Binary Cross-Entropy Loss and the Adam Optimizer.

```python
train_loader = DataLoader(train_dataset, batch_size=256, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=256)

# device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# model + optimizer + loss
model = NeuralCF(num_users, num_items).to(device)
criterion = nn.BCELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)

# train loop
for epoch in range(5):
    model.train()
    total_loss = 0
    for batch in train_loader:
        user = batch['user'].to(device)
        item = batch['item'].to(device)
        label = batch['label'].to(device)

        optimizer.zero_grad()
```

Figure 6. Neural Collaborator Filter

3. RESULTS

3.1. The Impact of N-BEATS Architecture on Forecasting

The forecasting model uses the N-BEATS architecture, a feedforward network composed of trend blocks and seasonality blocks. Its advantages include: no need for manual lag parameterization, insensitivity to input scale, support for multi-horizon forecasting without sliding windows, and greater stability and easier training compared to LSTM and ARIMA. This model delivers high accuracy even on noisy or missing data and offers high interpretability, as shown in Figure 7.

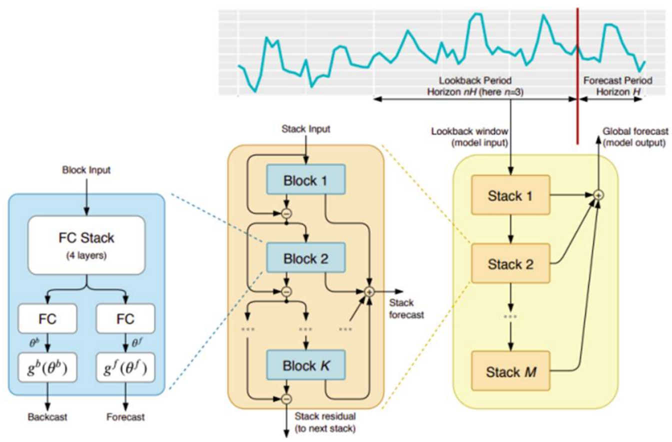

Figure 7. N-BEATS architecture illustration

3.2. Neural Collaborative Filtering Architecture

NCF architecture replaces traditional matrix factorization methods with deep learning. In the procurement context, this model predicts the compatibility between vendors and tenders based on historical interactions. Key features include the ability to capture non-linear relationships, support cold-start scenarios, and optimization using ranking metrics such as Hit Rate and NDCG. This model generates relevance scores to display tender recommendations that best match each vendor in Figure 8.

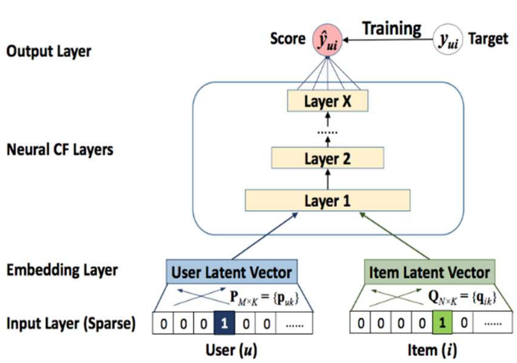

Figure 8. The general architecture of the NCF system is used

The system database is designed to support the core functions of the e-procurement platform, such as vendor account management, procurement request handling, and tag-based entity relationships, as shown in Figure 9.

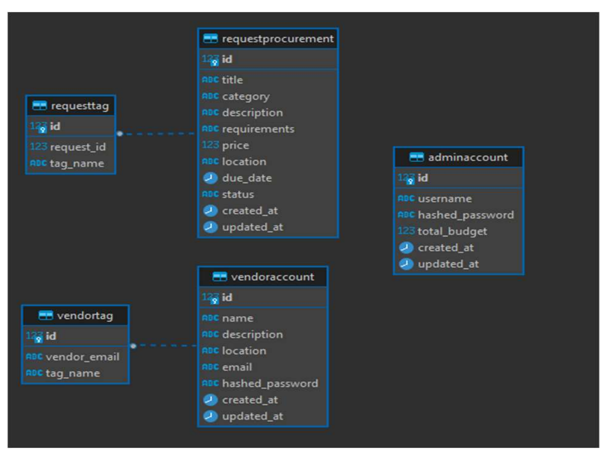

Figure 9. Database Schema

The database architecture uses a relational approach and is implemented with a SQL model (Python), combining SQLAlchemy and Pydantic for data validation. The five main tables in the database schema are: vendor account stores vendor account information and is linked to vendor Tag through a oneto-many relationship, vendor tag associates tags with vendor accounts to support search and classification based on service areas, request procurement Stores procurement request data, including details like price, deadline, and status; linked to request tag, request tag stores tags related to procurement requests to enable filtering and recommendation features, admin account represents admin accounts, storing access rights and total budget used for system control and validation. This database structure is designed not only for efficient data storage and access but also to support advanced features such as tag-based search, vendor recommendations, and machine learning model integration. With well-structured relationships, the system can be developed in a scalable way while remaining flexible for future analytical and automation needs. This web-based procurement system involves two main actors: admin and vendor, each with distinct roles, access rights, and features to support the procurement process. Actor: admin, the system manager**,** has full access to manage tenders, vendors, and budgets. Key features include View Dashboard, which provides a real-time summary of system status, including the Number of active tenders and ongoing projects; budget forecasting using the N-BEATS model; and Monthly/annual budget trend visualizations. Create Tender allows the admin to create and publish open tenders with complete details, including tags for automatic vendor matching. Create Direct Appointment**:** Enables direct procurement to a specific vendor without a bidding process, typically for urgent or low-value needs. View List of Tenders, view all active tenders, their statuses, and the list of vendors who have submitted bids. Includes recommendation scores generated by Neural Collaborative Filtering**.** View Direct Appointments Monitor the status of directly appointed projects and ensure transparent and centralized documentation in Figure 10.

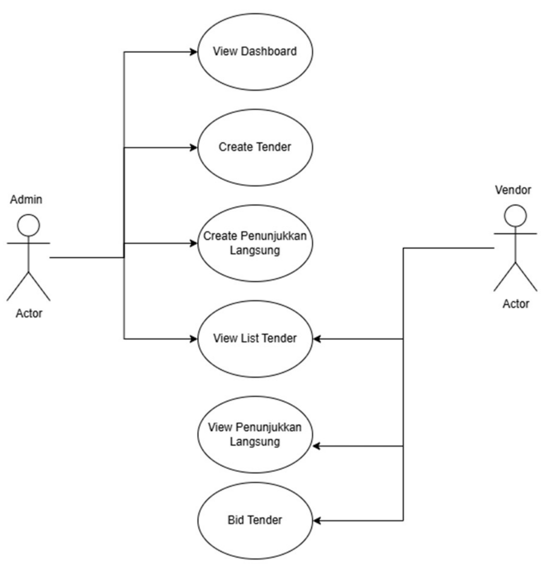

Figure 10. Case Diagram

This chapter discusses the results of the implemented system design and evaluates the performance of both the model and the system. The discussion covers the integration of the frontend, backend, machine learning models, and the database within the context of a procurement system. The evaluation of the NCF model is conducted using binary classification metrics such as Accuracy, Precision, Recall, F1-Score, and the Confusion Matrix, with the Movielens 100k dataset as a benchmark [17].

Meanwhile, the forecasting model using the N-BEATS method is evaluated using metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which reflect the accuracy of time-pattern predictions for relevant variables, such as the number of daily interactions. The forecasting model evaluation assesses the accuracy of procurement value predictions using historical data. Testing is conducted by comparing the predicted results with the actual data (ground truth) using appropriate visualizations and evaluation metrics. The visualization compares historical data (backcast), the model's predicted results (forecast), and actual data, providing a comprehensive view of the model's performance.

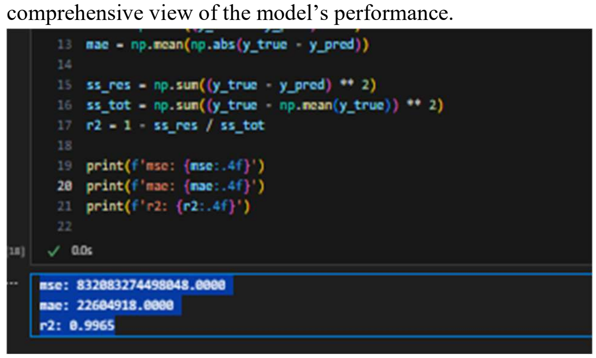

Figure 11. Evaluation Results of Several Common Metrics for Time Series Forecasting

The following are the evaluation results using common metrics for time series forecasting: Mean Squared Error (MSE): 8320, Mean Absolute Error (MAE): 22, R-squared (R^2): 0.9965. The relatively low MSE and MAE values indicate that the model's predictions are quite close to the actual values. Meanwhile, the very high R^2 value, close to 1, indicates that the model explains most of the variance in the data. This demonstrates that the model performs very well on the procurement data in Table 1.

Table 1 Evaluation Result of Model Neural Collaborative Filtering

Matrics	Value
Accuracy	68.81%
Precision (Kelas 0)	69.09%
Recall (Kelas 0)	55.67%
F1-Score (Kelas 0)	61.66%
Precision (Kelas 1)	68.65%
Recall (Kelas 1)	79.58%
F1-Score (Kelas 1)	73.71%

The model achieved an accuracy of 68.81%, indicating a fairly good ability to predict user interactions, although there is still room for improvement. Precision and recall for class 1 (users who like the item) are higher than for class 0, indicating that the model is more reliable at identifying user interest. However, the lower recall for class 0 (55.67%) highlights a weakness in detecting user disinterest (with a higher number of false negatives). The F1-score indicates moderate performance for both classes, with the positive class generally higher. These findings reflect common challenges in handling imbalanced implicit feedback datasets and support the literature stating that the Neural Collaborative Filtering (NCF) method delivers competitive performance.

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However, it requires additional approaches such as negative sampling, regularization, and model assembling to achieve optimal results [18]. Below is the Procurement List displayed after being scored using Collaborative Filtering (CF).

Figure 12. Scored Procurement List Results

An admin dashboard is available, displaying a line chart of forecasting results that visualizes the trend in procurement volume over time. This visualization provides dynamic insights to support more accurate adjustments to procurement strategies.

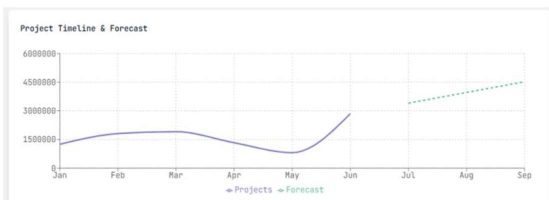

Figure 13. Admin Dashboard Displaying a Line Chart

4. DISCUSSION

The combined evaluation of Neural Collaborative Filtering (NCF) and forecasting reflects two complementary approaches in modern recommendation systems. NCF focuses on predicting static user-item interactions, whereas forecasting enables the system to adjust recommendations in response to changing trends and seasonality [17]. Given that NCF performance still needs improvement, particularly in reducing false negatives in class 0, integrating forecasting is key to enhancing the system's real-time responsiveness to user behaviour [19]. Deeper evaluation also opens opportunities to explore advanced metrics, such as the weighted F1-score, to address data imbalance.

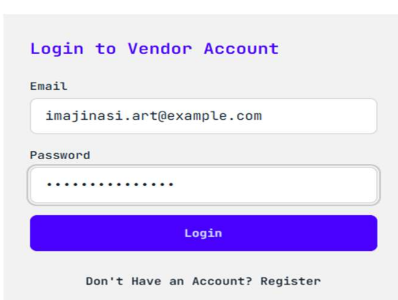

Figure 14. Login User

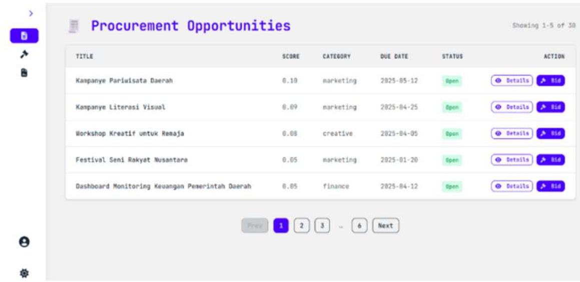

Figure 15. Procurement Recommendation List Display

The system displays a login page as the entry point for vendors to access features such as viewing tenders, submitting bids, and monitoring their participation status. The interface is designed to be simple and functional, with email and password input fields, a login button, and a registration link for new vendors. The system presents a list of procurement opportunities personalized using a hybrid recommendation approach that combines Neural Collaborative Filtering (NCF) and Content-Based Filtering (CBF). The goal is to enhance the relevance of tender results by tailoring them to each vendor's interests, history, and competencies. The system interface displays a tender project table with columns for project title, relevance score, category, due date, status, and actions to view details or submit a bid. The recommendation system uses a hybrid approach, combining Content-Based Filtering (CBF) and neural Collaborative Filtering (NCF): CBF builds vendor profiles based on explicit attributes such as tender categories, previously awarded projects, frequently accessed keywords, location, and project scale [16]. Similarity is calculated using methods like TF-IDF and cosine similarity. NCF learns latent interaction patterns between vendors and projects using embedding layers, aiming to predict future interaction relevance based on historical data [20]. This combined approach is intended to enhance the accuracy and relevance of tender recommendations presented to vendors.

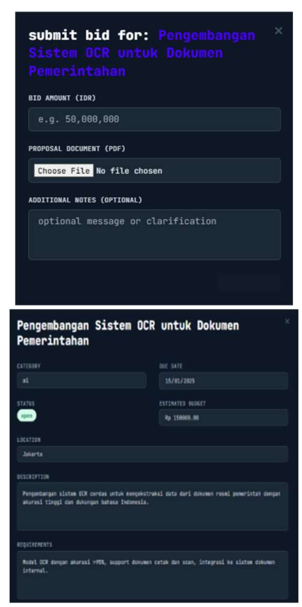

Figure 16. Implementation of NFC (Neural Collaborative Filtering)

The procurement system features a minimalist, intuitive, and mobile-friendly sidebar, allowing vendors to easily switch

between key features. This sidebar consistently appears on the left side of the screen and consists of three main menu items: Available Tenders – displaying active tenders filtered and recommended through a hybrid approach (NCF + CBF); Direct Appointments – listing directly appointed projects, useful for small-scale or urgent procurements; and my submissions – showing the vendor's bid history, including status and document details. At the bottom of the sidebar, there are additional menu options:
User Profile, for managing account settings and interaction history, and System Settings, for adjusting display preferences, notifications, and logging out.

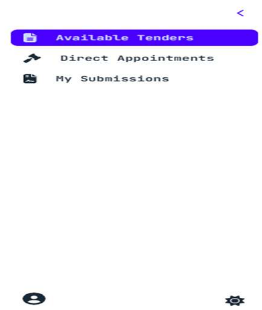

Figure 17. Sidebar

Visually, the design uses high contrast icons, purple as the indicator for the active state, and ample spacing to ensure usability on mobile devices. With its simple, functional navigation structure, the system supports an efficient user experience (UX) focused on key tasks: finding projects, submitting bids, and tracking project status. The system features a direct appointments function and a procurement mechanism in which vendors are selected without going through an open tender process. This feature is intended for special conditions such as urgent needs or highly specific, small-scale projects. Each item in the direct appointment list includes the following information: project title, awarding institution and deadline, appointed vendor name, brief description of the work scope, status or badge such as invited, indicating that the vendor has been officially invited to take on the project.

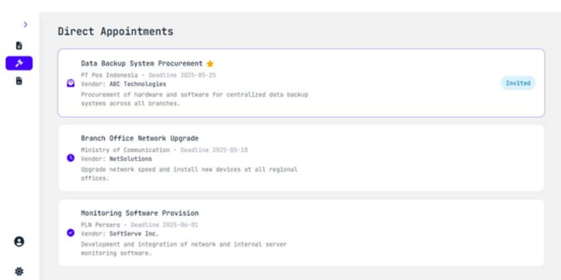

Figure 18. Display of the Direct Appointment Feature

This feature supports efficiency and transparency in non-tender procurement processes.

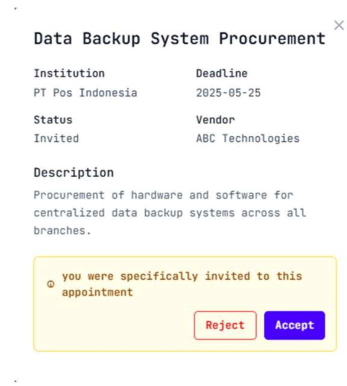

Figure 19. Project Description Display

The Submissions feature serves as a control center for vendors to monitor their entire project application history, including project title, institution, deadline, procurement type, and current status. The concise table layout, along with the use of colors and visual labels (e.g., blue for *submitted*, green for *accepted*, red for *rejected*), helps users quickly understand the status without reading each row in detail. Procurement types are also visually differentiated, such as gray for open tenders and purple for direct appointments.

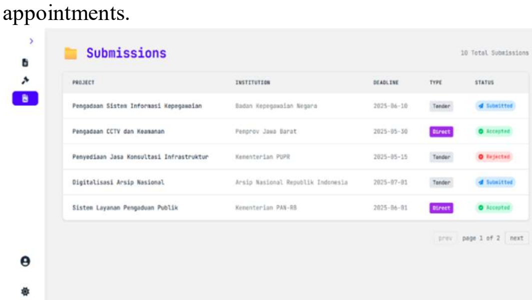

Figure 20. Fitur Submissions Display

This feature also supports pagination to maintain performance with large data volumes and to facilitate easy navigation between pages. It enhances transparency and efficiency, enabling vendors to make strategic decisions based on the status of their submissions. Additionally, a dedicated interface for administrators is provided to manage new procurement requests in a structured manner. The form includes fields such as project title, category, tags, due date, location, budget estimate, and detailed description. The system enforces standardized input formats with placeholders, clear labels, and validations, while the tags feature enhances recommendation accuracy through enriched metadata [21]. Important notes for admins: use standardized, unambiguous input formats; select tags commonly used in the industry; and write clear, complete project descriptions to avoid miscommunication during the bidding process. Overall, these two features, submissions and the admin form, strengthen the effectiveness, accuracy, and trustworthiness of the digital procurement system.

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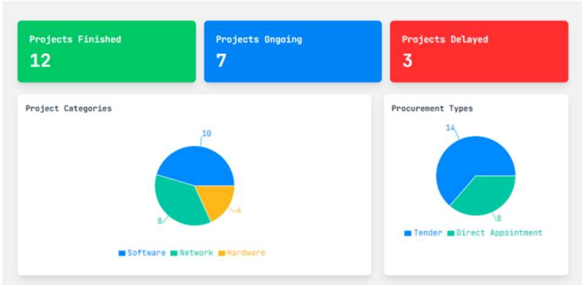

Figure 21. Procurement Dashboard

This dashboard provides a concise, comprehensive overview of the status of the institution's procurement project. Through informative visual displays and communicative use of color, administrators can quickly grasp the current situation without manually browsing through data. The dashboard features three key metrics and two pie charts. The three key metrics include: projects finished (12), displayed with a green background as an indicator of system success; projects ongoing (7), shown in blue, representing active progress; and projects delayed (3), marked in red as a warning signal for immediate action. The two pie charts include: project category distribution: software (10), network (8), hardware (4), useful for identifying procurement sector trends. Procurement Types: Tender (14), direct appointment (8) enabling evaluation of the balance between transparency and efficiency. This dashboard serves not only as a monitoring tool but also as support for strategic decision-making. The combination of key metrics, data visualization, and color usage makes the system effective, informative, and responsive to the dynamics of procurement projects.

Figure 22. Budget Forecasting Display

This visualization combines two layers of information in a single chart: the actual monthly project values (solid purple line) and the projected future values (dashed green line). The projections are generated using the N-BEATS predictive model, which was chosen for its fully data-driven nature and flexibility in handling non-periodic or fluctuating data. Reasons for choosing N-BEATS: does not require trend or seasonal assumptions, effectively captures non-linear patterns, and is more adaptive than models like ARIMA or Prophet in the context of e-procurement [8]. Results and benefits: the chart shows a peak in project value in March, followed by a sharp decline through May. The model projects that the downward trend will continue if no new interventions occur. This projection functions as an early warning system, prompting administrators to evaluate strategies if a decline is anticipated. The integration of N-BEATS into the dashboard enables the system not only to reflect historical data but also to forecast the future. This supports more proactive and adaptive decision-making, such as scheduling major tenders during predicted low periods or allocating budgets more strategically based on projected project performance.

Figure 23. Project Keywords Display

This visualization displays a word cloud highlighting the most frequent keywords in project documents, tender descriptions, and other procurement-related activities. Although it appears simple, the word cloud is the result of a complex text-mining process aimed at identifying linguistic patterns and dominant contexts within the procurement process. The words "software" and "negotiation" appear in larger sizes, indicating their high frequency. This suggests that the most dominant procurement projects involve software development. Negotiation is a critical phase in the procurement cycle, involving aspects such as pricing, scope, and timeline. This word cloud is not just a visually engaging representation but also provides quick insights into the main focus and dynamics of procurement activities, serving as a foundation for future strategic or policy evaluation.

5. CONCLUSION

Based on the results of system development and implementation, the main conclusion is that digital transformation in the procurement of goods/services can be significantly enhanced through the implementation of a web-based system. This is evident from the increased efficiency in the submission, recording, and monitoring processes compared to previous manual methods. The N-BEATS model used for budget forecasting demonstrated excellent predictive performance, with an R^2 of 0.9965, an MAE of 22, and an MSE of 8320. This indicates that the system is highly accurate at identifying budget trends from historical data. The Neural Collaborative Filtering model provided a solid foundation for a recommendation system capable of classifying vendors and procurement needs in a relevant manner. However, there is still room for improvement, particularly in the recall of the negative class. The model has proven effective in generating recommendations that improve vendor compatibility with procurement projects. The developed system not only provides operational functionality but also supports strategic functions such as long-term planning, performance monitoring, and mitigating the risk of procurement failure through a forecasting dashboard and project status evaluation. System evaluations from both technical (response time, backend-frontend integration, ML model stability) and functional (user acceptance testing) perspectives show that the system effectively meets internal user needs. User satisfaction is categorized as very good based on a simple survey of procurement staff. With its modular and scalable architecture, the system has the potential to be implemented in other Pos Indonesia branches and to serve as a prototype for a national AI- and data-driven smart procurement platform.

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