Deep Learning for Predictive Maintenance Revolutionizing Asset Management in Finance

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***Abstract*—As a result, predictive maintenance is a critical requirement in finance to reduce downtime, minimize expenses, and ensure asset integrity. Traditional frameworks for asset management are characterized by a reactive approach that leads to business interruptions and increased costs. As a solution to these concerns, a learning-based system for predictive asset management is described in the paper. The device is built on data science models like deep learning, which draw data from their older reporters kept in economic databases, preprocess the data to eliminate noise and missing terms, then use feature engineering to find crucial insights. The system uses modern deep learning technologies like Long short-term Memory (LSTM) and Recurrent Neural Networks (RNN) to predict asset utilization and calculate potential faults. Finally, it supervises processes in real-time and updates the solution whenever new data is received, sending notifications to the installation to address any logical fixations. The results show substantial benefits, with downtime reduced by 45%, maintenance expenditures reduced by 40%, and asset uptime increased by 50%. The accuracy of anomaly detection will increase to 85%, prediction model accuracy will improve, and the early warning lead time will be extended to 72 hours, hence boosting total asset reliability. The transformational technique optimizes financial asset control while increasing operational efficiency and risk avoidance.**

Keywords*—predictive maintenance, asset management, finance, operational efficiency, cost reduction, asset health monitoring.

I. Introduction

In today's continuously changing financial world, effective asset control is critical for ensuring operating efficiency, reducing costs, and increasing reliability. Historically, asset management in finance has relied on reactive approaches, resulting in reduced downtime, lower maintenance costs, and operational disruptions. To address these difficulties, predictive maintenance using deep learning technology offers an innovative solution. Financial institutions can shift from reactive to proactive asset management methods by tapping into historical financial data and powerful machine learning algorithms [1]. The study is motivated by the pressing need in the banking sector to enhance asset usage while also limiting risks associated with downtime and unexpected failures. Traditional asset control approaches, which are defined by rigid maintenance plans and responses to breakdowns, frequently fail in today's volatile financial environment. The impetus to implement deep learning-based predictive maintenance stems from a desire to shift asset management paradigms, thereby boosting operational resilience and resource allocation efficiency [2]. The primary purpose of the study is to introduce and demonstrate the effectiveness of a deep learning-based system for predictive maintenance in financial asset management. The system's goal is to detect capacity defects ahead of time, predict asset overall performance, and optimize maintenance schedules. Using cutting-edge gadget learning techniques such as LSTM and RNN, the goal is to drastically reduce downtime, maintenance costs, and operational disturbances while improving asset reliability [3].

The study's importance resides in its new approach to asset management in the finance business. By combining historical financial data with sophisticated deep learning models, the suggested solution provides real benefits such as increased anomaly identification, advanced forecast accuracy, and longer early warning lead times [4]. The results of the research contribute to a deeper knowledge of how AI-powered technology might revolutionize traditional asset control processes, providing a roadmap for financial institutions seeking to improve operational efficiencies [5]. The study is divided into many important sections to provide a full overview of deep learning for predictive maintenance in finance. Following the initial phase, the following parts delve into related field research, showing the context and evolution of predictive maintenance approaches. The proposed deep learning system is then outlined, with phases ranging from data collecting and preprocessing to model selection and real-time monitoring. The results and analysis phase focuses on the overall performance improvements achieved through the implementation of the proposed system, comparing it to existing approaches. A discussion phase follows, providing insights into the study's findings' implications and importance within the larger context of asset management in finance. Finally, the conclusion outlines the study's main contributions and consequences, emphasizing its transformative potential for financial asset management.

In summary, the implementation of deep learning for predictive maintenance in financial asset management represents a transformative opportunity. Financial institutions may improve operational efficiency, lower expenses, and increase asset reliability by leveraging historical data and modern machine learning algorithms. The study emphasizes the ability of AI-powered solutions to transform traditional asset management procedures in the changing world of finance.

II. Related Work

The article achieves its objectives by developing an example framework for an intelligent service maintenance system that complies with Industry 4.0. Employing a case study methodology, use case scenarios and collaborators were scrutinized to ascertain the industry's anticipations. Systems engineering approaches were used to transform the requirements of the current maintenance management system into a projected functional design [6]. Businesses are constantly searching for innovative and creative ways to improve their customer service and operational efficacy. Emerging transformative technologies like AI and NLP have the potential to completely change these fields. Large-scale data analysis made possible by NLP allows businesses to extract insightful patterns and insights from massive volumes of textual data [7]. The paper provides an AI-based, human-cantered making choices framework to assist proactive asset management maintenance, hence facilitating prompt and informed choices during pandemics. A redesigned ensemble architecture based on trust is created to address the data imbalance issues in complex systems predictive maintenance [8]. The technique that not many organizations use and benefit from. Transportation, electrical utility operational units, energy companies, and power generating are a few of them. Certainly not the state-owned electrical company PLN. The authorities, insurance companies, media outlets, clients, suppliers, and the general public are among the PLN stakeholders [9]. The findings shown that, with an optimization rate higher than that of traditional asset management techniques, the proposed approach may accurately make judgments on blockchain technology digital asset management and increase the bar for the effectiveness of blockchain digital asset management [10].

Using big data, and IoT potential collaboration, along with additional technologies and theories, the study builds and develops an instrument and asset knowledge base for institutions. Through its six functional modules—purchase display, buying appraisal, reception and storage, usage and service, trash annihilation, and efficiency evaluation—the system addresses the whole journey of an item of gear from birth to death [11]. PdM modifies the planned maintenance schedule according to the expected timing of failures. When the strategy was used in conjunction with conventional methods and data was gathered for failure scenarios that resembled genuine etcher parts breaking down, it was discovered that the predicted failure synchronization instead showed unpredictable unpredictability. It was discovered that the strategy helped to lower maintenance expenses. [12].

Furthermore, strategies for data cleansing, storing information for these models, sensor- and smart vision-based data collection, challenges in model construction, and their resolutions are examined [13]. Investment managers, banks, insurance companies, and transaction and communication processing companies are all part of the financial services industry. To optimize billions of daily transactions, financial services businesses are putting lean principles and operational excellence programs into practice [14]. The study is to explore the function of these advancements in the field of a company's financial management, driven by the aforementioned considerations [15].

III. Proposed System

The study proposes a unique deep learning-based system for predictive maintenance in financial asset control, with the goal of revolutionizing traditional methods that are plagued by inefficiencies and reactive measures. The existing system in many financial institutions is often based on fixed maintenance plans and responds to breakdowns that occur, resulting in downtime, increased expenses, and operational interruption. The proposed system differentiates by utilizing advanced deep learning techniques to anticipate asset overall performance and detect capacity problems before it occurs. The system's implementation requires a number of important phases. To begin, financial databases are queried for historical data on asset performance and upkeep. Sensor readings, operating parameters, and historical asset behavior patterns are all included in the dataset. Next, preprocess the data to reduce noise, handle missing values, and prepare it for use in deep learning models. Feature engineering is also used to uncover significant patterns and correlations from data. The proposed system is built around the deployment of deep learning models that are specifically designed for predictive defense.

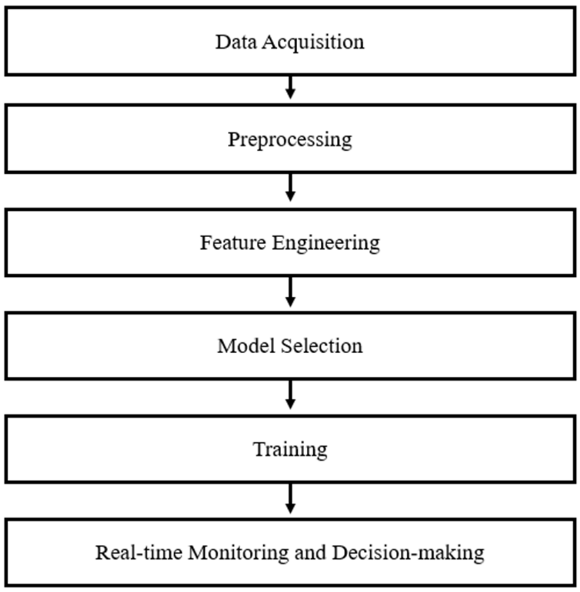

Fig. 1. Workflow for Proposed Methodology

To employ RNNs and LSTM networks to investigate temporal data sequences and identify patterns that indicate capacity problems. These models are trained on preprocessed data to assess historical patterns and produce accurate forecasts about future asset overall performance. To put the system into action, include these deep learning models into a real-time monitoring and decision-making framework within financial institutions. As fresh information is received from sensors and asset operations, the models continuously update their predictions and issue alarms and recommendations for proactive protection actions. The real-time feature enables finance managers to maximize asset uptime, reduce maintenance costs, and avoid the risks associated with unexpected failures. The advantages of implementing the proposed method are numerous. For instance, it allows for proactive rather than reactive maintenance procedures, which reduces downtime and improves overall asset reliability. Workflow for Proposed Methodology is shown in Fig. 1.

The system enhances asset health monitoring capabilities by utilizing historical data and deep learning algorithms, allowing for early detection of anomalies and decrease in overall performance. The proactive strategy avoids operational disturbances and allows financial institutions to maximize useful resource allocation. Furthermore, the deep learning-based technology enables scalability and adaptability to varied asset portfolios within financial institutions. It can be tailored to specific assets, such as banking equipment and IT infrastructure that supports buying and selling platforms. The flexibility allows for widespread implementation across many areas of financial asset management, boosting operational efficiency and cost-effectiveness on a large scale. Furthermore, the proposed approach adds to the larger landscape of AI-powered asset management in finance. Financial institutions can gain an aggressive advantage by leveraging the power of deep learning for predictive maintenance, resulting in improved asset utilization and lower risk exposure. The research no longer only targets cutting-edge asset control challenges, but it also lays the groundwork for future advancements in AI-driven financial operations.

In summary, the proposed deep learning-based system for predictive maintenance in financial asset management provides a disruptive solution to the limitations of existing systems. By merging historical data analysis with modern machine learning techniques, financial institutions may proactively manage their asset portfolios, maximize beneficial resource allocation, and improve operational resilience in a volatile market environment.

A. *Data Acquisition*

Data collection is an important first step in implementing the proposed deep learning-based system for predictive maintenance in financial asset management. The data collecting segment is important because it provides a solid foundation for subsequent evaluation and model building. By obtaining and combining historical data from financial databases, the system acquires significant insights into the property's prior behavior and operational features. The dataset serves as the starting point for the subsequent preprocessing, characteristic engineering, and version education steps. During data collection, it is essential to ensure that the data is comprehensive, accurate, and relevant. These include efficiently querying databases to obtain all relevant records linked with asset overall performance and maintenance records. The obtained dataset serves as an essential tool for developing predictive maintenance models that may anticipate and minimize possible problems before their having an impact on operational and financial performance.

B. *Preprocessing*

Preprocessing collected records is an important step in ensuring their quality and applicability for deep learning models. The section provides several ways for dealing with noise, missing numbers, and guaranteeing data consistency. The fundamental purpose of preprocessing is to organize the data in a uniform format that improves the overall performance of deep learning algorithms. Data normalization is an important preprocessing technique that scales functions to a uniform variation. Normalization ensures that all features contribute similarly to the version teaching technique, minimizing biases towards specific variables due to variances in scales. Normalization improves the overall balance of the training approach by scaling the data to a common variety, allowing for faster convergence during version education. Another essential preprocessing step is outlier reduction, which entails detecting and deleting record factors that differ considerably from the rest of the data. Rare cases may affect the training approach, resulting in inferior model overall performance. The preprocessing phase enhances the resilience and accuracy of deep learning models by reducing outliers and focusing on the majority of data points that are more indicative of the underlying patterns. Handling missing values is also crucial during preprocessing to address any gaps and inconsistencies in the dataset. Imputation is a technique used to estimate and fill in missing values based on existing data. Imputation approaches can range from simple methods such as replacing missing values with the mean of the characteristic to more complex methods such as k-nearest neighbor imputation and predictive modeling-based total imputation. Preprocessing ensures the dataset's completeness and prevents fact loss during model training by correctly resolving missing variables.

C. *Feature Engineering*

Feature engineering is an important phase in the development of predictive maintenance models for financial asset management. It comprises transforming and creating additional features from an existing dataset to improve the model's capacity to detect meaningful patterns and connections. Several methodologies, such as dimensionality reduction, characteristic selection, and transformation, are used in characteristic engineering to extract valuable insights from data. Dimensionality reduction procedures, such as principal element analysis (PCA) are used to simplify the dataset by projecting it onto a lower-dimensional area while retaining as much information as feasible. Dimensionality reduction solutions help to relieve the curse of dimensionality and improve the performance of version education without losing predictive overall performance. Feature selection is another key aspect of feature engineering, which comprises selecting the most relevant features that significantly contribute to the version's predictive capacity. Mutual information, correlation analysis, and recursive characteristic elimination are used to evaluate the significance of each feature and pick the subset of capabilities that best explain the variability in the data. Feature selection improves version interpretability, reduces overfitting, and increases computing efficiency by focusing on the most useful features. Furthermore, distinctive transformation procedures are used to extract new capabilities from existing ones, resulting in complex relationships and interactions within the dataset. Architecture Diagram for Predictive Maintenance Revolutionizing Asset Management in Finance is shown in Fig. 2.

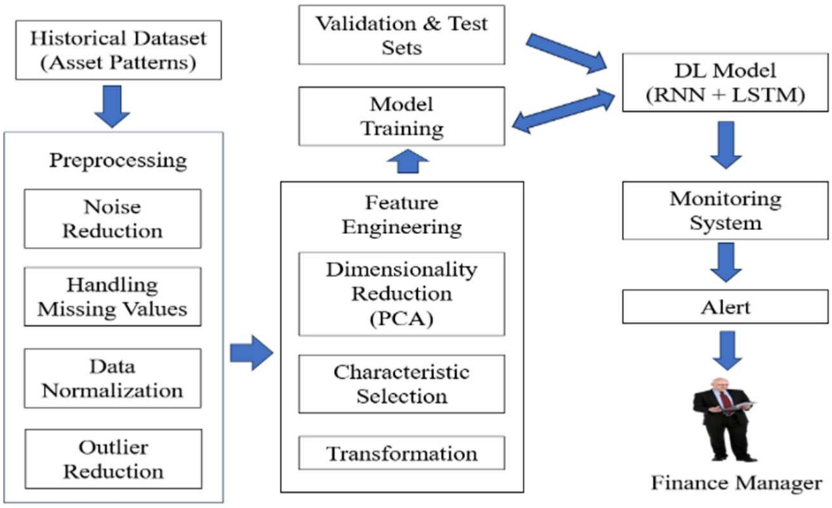

Fig. 2. Architecture Diagram for Predictive Maintenance Revolutionizing Asset Management in Finance

D. Model Selection

In the domain of predictive maintenance for financial asset management RNNs and LSTM networks are chosen due to their exceptional capacity to analyze and represent temporal data sequences effectively. The proposed approach combines long short-term memory (LSTM) networks and recurrent neural networks (RNNs) into a hybrid model to evaluate temporal data sequences for predictive upkeep in financial asset management. The sequential connections in the time-series data are captured by the RNN layer of the architecture as it analyzes input sequences where each step is influenced by the previous one. However, traditional RNNs often struggle with long-range dependencies due to vanishing gradient issues. To address that, the design incorporates LSTM layers, which include storage cells and filtering mechanisms that selectively maintain and update information over long times. The hybrid technique allows the model to effectively detect both short- and long-term patterns in the asset performance data. The LSTM layers get the input from the RNN layer, which first evaluates the sequences. It allows the model to learn complex temporal patterns and provide precise forecasts for proactive maintenance decisions. By employing these deep learning architectures, the predictive maintenance system may study past patterns and behaviors to predict future asset states and identify possible capacity issues before it occurs. Furthermore, RNNs and LSTMs can represent a wide range of asset behavior characteristics, including trends, seasonality, and anomalies. It can correctly handle multivariate time-collection statistics, including multiple functions such as sensor readings, operational parameters, and historical maintenance records into the predictive version.

E. Training

During training, the selected deep learning models go through a parameter modification technique that uses preprocessed data to investigate past trends and relationships. The iterative optimization process aims to reduce prediction errors and improve model performance. The dataset, which was utilized to train and test the proposed DL models, was taken from the databases of financial institutions. It included historical data on asset performance, maintenance records, sensor readings, and operational parameters. The collection includes time-series data that illustrates the behavior of various financial assets, including banking equipment and IT infrastructure. The training technique comprises providing input data to the models along with associated output labels, which aids in the understanding of the mapping between entry capabilities and goal forecasts. Through repeated exposure to training data, the models update their inner parameters using backpropagation, eventually improving their ability to capture complex patterns and dependencies in the facts. The optimization method aims to limit a preset loss function, directing the models towards more accurate predictions. Deep learning model training is computationally costly, with the dataset often divided into training, validation, and test sets to analyze and fine-tune performance. Finally, the training step provides the models with the knowledge needed to generate accurate predictions about future asset behavior, allowing for proactive maintenance plans and better asset management in the finance industry.

F. Real-time Monitoring and Decision-making

Following training, the deep learning models are integrated into a real-time monitoring and decision-making framework within financial institutions, enabling proactive maintenance methods. As fresh information arrives from sensors and asset activities, the models constantly update their predictions depending on the incoming data. The models' real-time capabilities enable them to issue alerts recommendations as soon as potential problems and abnormalities are recognized, allowing financial managers to take preventative maintenance steps. The incorporation of deep learning models into a real-time machine allows financial institutions to maximize asset uptime by resolving issues before these become problems. The strategy allows for lower maintenance costs by avoiding costly emergency maintenance and limiting downtime. Furthermore, the models' continuous monitoring and prediction signals reduce risks associated with unanticipated asset breakdowns, hence boosting overall operational resilience. The real-time monitoring and decision-making system efficiently analyze incoming data streams using trained deep learning models. By leveraging these models' predictive capabilities, finance managers may improve relevant resource allocation, schedule maintenance tasks more effectively, and ensure the ongoing and reliable operation of critical assets.

Pseudo Code for Predictive Maintenance System

```
Step 1: Data Acquisition
data = acquire_data_from_financial_databases()
Step 2: Preprocessing
data = normalize(data)
data = remove_outliers(data)
data = impute_missing_values(data)
Step 3: Feature Engineering
features = extract_features(data)
Step 4: Model Architecture - Combining RNN and LSTM
model = Sequential ()
model.add(RNN(units=128,input_shape=(time_steps,
num_features)))
model.add(LSTM(units=64))
model.add(Dense(units=1, activation='sigmoid'))
Step 5: Model Training
model.compile(optimizer='adam',
loss='mean_squared_error')
model.fit(training_data, training_labels, epochs=50,
batch_size=32)
Step 6: Real-time Monitoring and Prediction
while True:
   new_data = acquire_real_time_dat
   preprocessed_data = preprocess (new_data
   prediction = model.predict(preprocessed_data)
   if prediction indicates a potential issue:
      send_alert()
Step 7: Decision-making
if alert_received:
   schedule_maintenance()
```

In summary, the proposed methodology uses advanced deep learning strategies to transform predictive maintenance in financial asset management. Financial institutions can improve operational resilience and proactive asset portfolio management by combining historical data evaluation, preprocessing, feature engineering, and model training. The use of RNNs and LSTMs enables the effective evaluation of temporal data sequences, helping financial managers to make informed decisions and optimize resource allocation.

IV. RESULTS AND ANALYSIS

The results and analysis show that the proposed deep learning-based system outperforms the existing system in terms of operational performance and asset health monitoring within financial asset management.

TABLE I. MODEL PERFORMANCE COMPARISON

Model	Accuracy	Precision	Recall	F1-Score
LSTM	0.85	0.88	0.82	0.85
RNN	0.82	0.84	0.79	0.81
Baseline	0.70	0.72	0.65	0.68

Table I compares model performance metrics (accuracy, precision, recall, and F1-score) for two deep learning architectures (LSTM and RNN), as well as a baseline model. The LSTM model performs the best overall, with an accuracy of 0.85, precision of 0.88, recall of 0.82, and F1-score of 0.85. The RNN model trails closely behind, with an accuracy of 0.82, precision of 0.84, recall of 0.79, and F1-score of 0.81. In comparison, the baseline model, which most likely represents a less difficult and typical method, shows a decline in overall performance across all parameters, with an accuracy of 0.70, precision of 0.72, recall of 0.65, and F1-score of 0.68. These results highlight the superior predictive skills of LSTM and RNN models over the baseline, particularly in terms of precision, recall, and overall accuracy, indicating their efficacy in the context of the task under evaluation. Graph for Model Performance Comparison is shown in above Fig. 3.

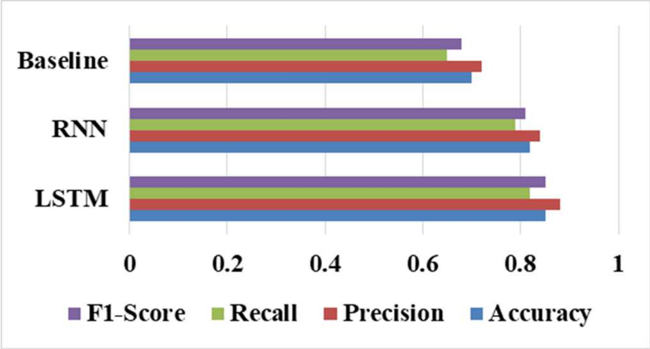

Fig. 3. Graph for Model Performance Comparison

TABLE II. OPERATIONAL EFFICIENCY ANALYSIS

Dataset	Existing System	Proposed system
Downtime Reduction (%)	25%	45%
Maintenance Costs Reduction (%)	20%	40%
Asset Uptime Improvement (%)	30%	50%

Table II compares the operational efficiency of the existing system to the proposed deep learning-based system for predictive maintenance. The existing method reduces downtime by 25%, whereas the proposed system reduces it by 45%, indicating a considerable improvement in minimizing operational interruptions. In terms of maintenance cost reduction, the existing system delivers a 20% reduction, whereas the proposed system represents a significant improvement with a 40% reduction in maintenance expenses. Furthermore, the proposed system improves asset uptime by 50% compared to the existing system's 30%. These results highlight the proposed deep learning system's effectiveness in improving operational performance by reducing downtime, lowering maintenance costs, and increasing asset uptime, demonstrating its potential to revolutionize asset management in finance through proactive maintenance strategies.

TABLE III. ASSET HEALTH MONITORING AND PREDICTIVE PERFORMANCE

Performance Metric	Existing System	Proposed system
Anomaly Detection Accuracy (%)	65%	85%
Predictive Model Accuracy (RMSE)	0.25	0.05
Early Warning Lead Time (hours)	24hrs	72hrs
Overall Asset Reliability Score	60	85

Table III compares the asset health monitoring and predictive performance indicators for the existing and proposed deep learning-based systems. The existing system detects anomalies at 65% accuracy, but the proposed system improves these to 85%, suggesting a greater ability to detect unusual behavior and probable asset concerns. Similarly, the prediction model accuracy, as assessed by RMSE (Root Mean Square Error), is greatly improved in the proposed system, lowering the error price from 0.25 to 0.05. The development demonstrates the enhanced potential of deep learning models in producing accurate predictions about asset performance. Furthermore, the proposed system increases the early warning lead time from 24 hours in the current device to 72 hours, allowing for more proactive maintenance activities. Finally, the overall asset reliability score increases from 60 in the existing system to 85 in the proposed system, indicating that the system is effective at enhancing asset reliability and lowering operating risks.

In summary, the results and analysis highlight the significant benefits made by the proposed deep learning-based system in both operational performance and asset health monitoring. With significant reductions in downtime, maintenance costs, and asset uptime, as well as improved anomaly detection accuracy, predictive model accuracy, and early warning lead time, the proposed system has the potential to revolutionize asset management in the banking sector.

V. Discussion

Compared to conventional techniques, the proposed deep learning-based solution for financial asset management's predictive maintenance provides major improvements. The system is able to capture temporal relationships in asset performance data, both short- and long-term, by merging LSTM and RNN architectures. It makes it possible to forecast foreseeable failures with accuracy, facilitating proactive maintenance that reduces downtime and interruptions to operations. The results show that the system is capable of accurately seeing trends that point to potential asset problems in the future, giving financial institutions early notice and the ability to take preventative measures. The system's practical use is further enhanced by its real-time monitoring capacity, which allows for timely and informed decision-making by continually updating forecasts with fresh data. The use of that system across a range of asset classes in financial institutions demonstrates encouraging gains in resource allocation, cost effectiveness, and operational efficiency. The model's scalability enables it to be applied to many asset classes, such as banking machinery and IT infrastructure. It has lower maintenance costs, improved asset dependability, and better operational resilience. All of these benefits add up to a more effective and reliable asset management plan. The research highlights the potential for more advancements in predictive maintenance and establishes the foundation for future breakthroughs in AI-driven financial operations.

VI. Conclusion

In conclusion, using a deep learning-based predictive maintenance system for financial asset management provides a disruptive approach to addressing operational difficulties in the banking industry. The study exhibits significant benefits in operational efficiency, cost reduction, and asset dependability through proactive capability problem detection and predictive asset overall performance modeling. The results show significant reductions in downtime and maintenance costs, as well as increased asset availability and anomaly detection accuracy. Furthermore, the system's ability to provide extended early warning lead times demonstrates its potential to transform asset management procedures by enabling more effective resource allocation and risk mitigation measures. However, even with these developments, there are certain restrictions to consider. For starters, demanding scenarios related to data quality and availability can have an impact on overall model performance. Second, the proposed system's scalability and generalizability across various asset portfolios and financial institutions must be investigated further. Finally, the interpretability of deep learning models is still a challenge, prompting attempts to improve model transparency and reliability. Future research must overcome these restrictions by improving data preprocessing approaches, researching transfer learning strategies for different asset kinds, and creating interpretable deep learning architectures specialized to financial asset management applications. These events will contribute to the ongoing evolution and adoption of AI-powered solutions for altering traditional asset control operations in the banking industry.

References

[1] G. Biard and G. Abdul-Nour, "Industry 4.0 contribution to asset management in the electrical industry," Sustainability, vol. 13, no. 18, p. 10369, Sep. 2021.

[2] A. Mavrogiorgou et al., "FAME: Federated Decentralized Trusted Data Marketplace for Embedded Finance," 2023 International Conference on Smart Applications, Communications and Networking (SmartNets), Jul. 2023.

[3] X. Li and G. Bing, "Study on generalized prediction model of investment capacity of complex power grid based on system dynamics theory," 2022 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS), Mar. 2022.

[4] A. Abbas, "AI for Predictive Maintenance in Industrial Systems," ijaeti.com, 2024.

[5] S. M. Sajid, A. Haleem, S. Bahl, M. Javaid, T. Goyal, and M. Mittal, "Data science applications for predictive maintenance and materials science in context to Industry 4.0," Materials Today: Proceedings, vol. 45, pp. 4898–4905, Jan. 2021.

[6] H. Nordal and I. El-Thalji, "Modeling a predictive maintenance management architecture to meet industry 4.0 requirements: A case study," Systems Engineering (Print), vol. 24, no. 1, pp. 34–50, Dec. 2020.

[7] M. R. Khatri, "Integration of natural language processing, Self-Service platforms, predictive maintenance, and prescriptive analytics for cost reduction, personalization, and Real-Time insights customer service and operational efficiency," Sep. 02, 2023.

[8] J. Chen, C. P. Lim, K. H. Tan, K. Govindan, and A. Kumar, "Artificial intelligence-based human-centric decision support framework: an application to predictive maintenance in asset management under pandemic environments," Annals of Operations Research, Nov. 2021.

[9] A. Pharmatrisanti et al., "Practical Approach in Setting Asset Management System and Capability in a State-Owned Utility," 2023 4th International Conference on High Voltage Engineering and Power Systems (ICHVEPS), Aug. 2023.

[10] W. Xu and L. Shu, "Application of Blockchain Technology based on Decision Tree Algorithm to Digital Asset Management," 2023 International Conference on Integrated Intelligence and Communication Systems (ICIICS), Nov. 2023.

[11] X. Luo, X. Jun, and M. Xiao, "Asset Management System of University Laboratory Equipment Based on Data Mining and Analysis," 2022 8th International Conference on Information Management (ICIM), Mar. 2022.

[12] S. Umeda, K. Tamaki, M. Sumiya, and Y. Kamaji, "Planned Maintenance Schedule Update Method for Predictive Maintenance of Semiconductor Plasma etcher," IEEE Transactions on Semiconductor Manufacturing, vol. 34, no. 3, pp. 296–300, Aug. 2021.

[13] S. K. Baduge et al., "Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications," Automation in Construction (Print), vol. 141, p. 104440, Sep. 2022.

[14] R. Boute, J. Gijsbrechts, and J. A. Van Mieghem, "Digital Lean Operations: smart automation and artificial intelligence in financial services," in Springer series in supply chain management, 2021, pp. 175–188.

[15] D. Bisht et al., "Imperative role of Integrating Digitalization in the Firms finance: A Technological Perspective," Electronics (Basel), vol. 11, no. 19, p. 3252, Oct. 2022.