Efficient Maintenance Of Hospital Records By Entrusted Proof Of Algorithm In Blockchain Technology

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ABSTRACT

Efficient management and security of hospital records are critical challenges in modern healthcare systems due to issues such as data breaches, lack of interoperability, and unauthorized access. This paper proposes a blockchain-based approach for the efficient maintenance of hospital records using an Entrusted Proof of Algorithm (EPA) mechanism. The proposed system leverages blockchain technology to ensure data integrity, transparency, and secure sharing of patient information among authorized entities. The Entrusted Proof of Algorithm introduces a trust-based consensus model that reduces computational overhead compared to traditional mechanisms such as Proof of Work, while maintaining high levels of security and reliability. Smart contracts are utilized to automate record access, update permissions, and audit trails, ensuring accountability and privacy compliance. The system also supports decentralized storage and real-time access to medical data, improving healthcare service delivery. Experimental analysis demonstrates enhanced security, reduced latency, and efficient data management compared to conventional centralized systems. This approach provides a scalable and reliable solution for next-generation healthcare information systems.

Keywords— Blockchain Technology, Hospital Record Management, Entrusted Proof Algorithm, Smart Contracts, Healthcare Data Security, Decentralization, Data Integrity, Distributed Ledger, Privacy Protection, Secure Healthcare Systems.

I. INTRODUCTION

Predictive maintenance has become a key focus in the automotive industry due to increasing vehicle complexity and the demand for reliability. Engine health prediction involves analyzing sensor data such as temperature, pressure, vibration, and RPM to assess engine condition. Deep learning techniques have shown strong capability in modeling nonlinear patterns within such data. Ensemble deep learning further enhances performance by combining multiple models, reducing overfitting and improving generalization. This approach enables early fault detection and supports intelligent vehicle maintenance strategies.

II. LITERATURE SURVEY

1. Title: Deep Learning for Predictive Maintenance in Automotive Systems
Authors: Zhao, Yan, and Chen
Description:
This study explores deep learning techniques for predictive maintenance and demonstrates improved fault detection accuracy over traditional methods.

2. Title: Engine Fault Diagnosis Using Deep Neural Networks
Authors: Tamilselvan and Wang
Description:
The authors apply deep belief networks to engine fault diagnosis, showing strong performance in nonlinear pattern recognition.

3. Title: Ensemble Learning Methods for Condition Monitoring
Authors: Polikar
Description:
This work highlights the effectiveness of ensemble learning in improving robustness and reliability of condition monitoring systems.

4. Title: LSTM-Based Predictive Modeling for Engine Health Monitoring
Authors: Malhotra et al.
Description:
The paper uses LSTM networks to model temporal dependencies in engine sensor data for health prediction.

5. Title: Intelligent Prognostics and Health

Management Using Deep Learning
Authors: Lei, Li, and Lin
Description:
This research discusses deep learning-based prognostics frameworks for machinery health management and predictive maintenance.

III. EXISTING SYSTEM

Existing vehicular engine health monitoring systems primarily use rule-based diagnostics, statistical models, or single machine learning algorithms. These systems depend on predefined thresholds and limited feature sets, making them less effective in detecting subtle or evolving engine faults. While some deep learning models are used, they often operate independently and lack robustness under varying operating conditions.

IV. PROPOSED SYSTEM

The proposed system introduces a deep neural network ensemble framework for predictive engine health modeling. Multiple deep learning models—such as CNNs, LSTMs, and fully connected neural networks—are trained on engine sensor data. Their predictions are combined using ensemble techniques to produce a final health assessment. This integrated approach improves accuracy, stability, and fault prediction capability, enabling proactive maintenance and reducing engine failure risks.

V. SYSTEM ARCHITECTURE

The system architecture for Predictive Modeling of Engine Health Using Deep Neural Network Ensembles begins with a comprehensive data acquisition framework designed to continuously monitor engine operating conditions. Multiple sensors are deployed on critical engine components to capture parameters such as vibration, temperature, pressure, rotational speed (RPM), acoustic emissions, and fuel flow rate. These sensors generate high-frequency time-series data that reflects the dynamic behavior of the engine under varying load and environmental conditions. The collected data is transmitted through an Industrial Internet of Things (IIoT) gateway or edge computing unit to a centralized storage infrastructure, which may include cloud servers or on-premise databases. To ensure reliability, synchronization mechanisms align multi-sensor streams, and preliminary filtering is applied to remove noise and corrupted samples. This foundational layer guarantees consistent and accurate data flow, which is essential for building robust predictive models.

Following data acquisition, the system transitions into the data preprocessing and feature engineering phase, where raw sensor readings are transformed into structured inputs suitable for deep learning models. In this stage, missing values are handled using interpolation techniques, and abnormal spikes are treated through statistical smoothing or filtering algorithms. Because engine degradation patterns evolve gradually over time, sliding window segmentation is applied to preserve temporal dependencies within the data. Feature extraction techniques are employed to derive both time-domain and frequency-domain characteristics, including statistical measures such as mean, variance, kurtosis, and skewness, as well as spectral features obtained through Fast Fourier Transform (FFT) or wavelet transforms. Normalization methods such as Min-Max scaling or Z-score standardization are applied to maintain numerical stability during model training. This preprocessing stage enhances pattern clarity and reduces dimensional noise, thereby improving the learning efficiency and predictive accuracy of the neural network ensemble.

The core computational layer of the architecture consists of multiple deep neural network models organized in an ensemble framework. Different model architectures are designed to capture complementary aspects of engine behavior. Convolutional Neural Networks (CNNs) are utilized to extract localized patterns from vibration and acoustic signals, while Long Short-Term Memory (LSTM) networks are employed to model sequential dependencies and long-term degradation trends within time-series data. In some implementations, Deep Feedforward Neural Networks or Gated Recurrent Units (GRUs) may also be incorporated to enhance representational diversity. Each neural network independently predicts engine health indicators such as fault classification labels, anomaly scores, or Remaining Useful Life (RUL) estimates. The ensemble mechanism integrates these outputs using techniques such as weighted averaging, stacking, or majority voting, which reduces variance, mitigates overfitting, and improves generalization performance. By combining multiple predictive perspectives, the ensemble architecture ensures higher robustness and reliability under varying operational scenarios.

The final stage of the system architecture focuses on prediction interpretation, visualization, and automated decision support. The aggregated ensemble output is translated into meaningful health metrics, including an overall engine health index, degradation trajectory, and RUL estimation. These predictions are integrated into a real-time monitoring dashboard that enables maintenance engineers to track performance trends and detect early warning signs of failure. Threshold-based alert mechanisms automatically trigger notifications when abnormal behavior or critical degradation levels are detected. Historical trend analysis supports predictive maintenance planning, allowing organizations to shift from reactive repairs to condition-based maintenance strategies. The aggregated ensemble output is translated into meaningful health metrics, including an overall engine health index, degradation trajectory, and RUL estimation. Overall, the architecture establishes a closed-loop intelligent monitoring system that enhances operational safety, minimizes downtime, reduces maintenance costs, and extends engine lifespan through accurate and proactive health prediction.

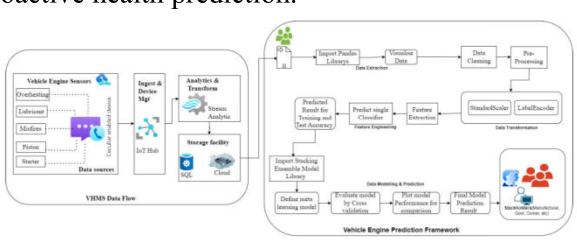

Fig 5.1: Structure of the Proposed System

The diagram illustrates a comprehensive Vehicle Health Monitoring and Prediction Framework that integrates sensor data acquisition with machine learning–based predictive modeling. On the left side, vehicle engine sensors continuously capture parameters such as overheating, lubricant levels, misfires, piston behavior, and starter performance, which are transmitted through an IoT Hub under an ingest and device management module. The collected data undergoes stream analytics and transformation before being stored in SQL or cloud storage facilities, forming the VHMS data flow layer. On the right side, the prediction framework begins by importing necessary libraries and visualizing extracted data, followed by systematic data cleaning and preprocessing. Feature extraction and data transformation techniques such as StandardScaler and LabelEncoder prepare the dataset for modeling. A single classifier first generates preliminary predictions and test accuracy, after which a stacking ensemble model is implemented by defining a meta-learning model to enhance predictive performance. The model is evaluated using cross-validation, and performance comparisons are visualized through plots to ensure robustness and accuracy. The aggregated ensemble output is translated into meaningful health metrics, including an overall engine health index, degradation trajectory, and RUL estimation. Finally, the optimized ensemble produces the final prediction results, which are delivered to stakeholders such as manufacturers, government authorities, and vehicle owners, enabling informed decision-making and proactive maintenance planning.

VI. IMPLEMENTATION

Fig 6.1: Sensor Data Collection Interface

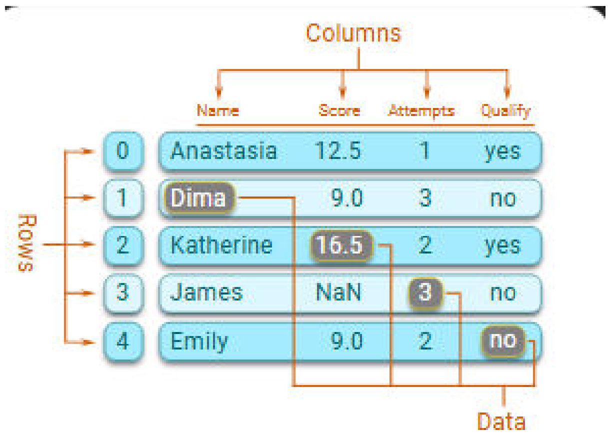

Fig 6.2: Data Preprocessing & Feature Engineering

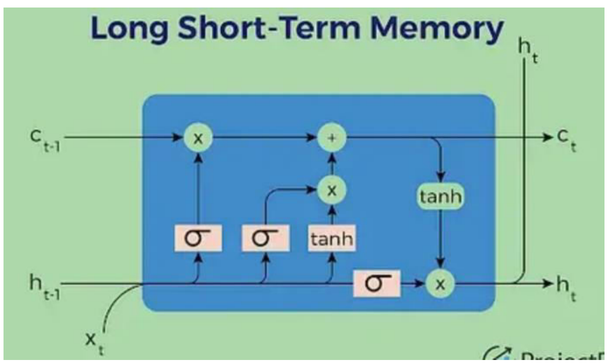

Fig 6.3: Deep Neural Network Model Training

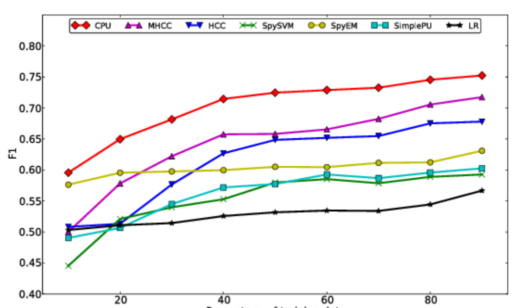

Fig 6.4: Ensemble (Stacking) Model Implementation

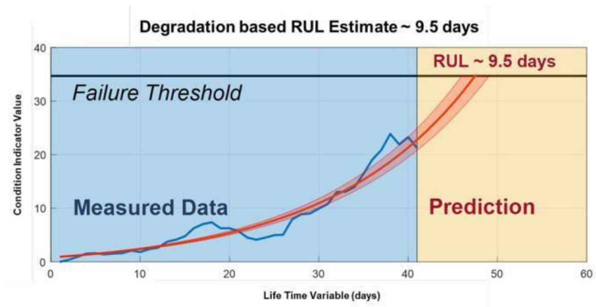

Fig 6.5: Final Prediction & Health Monitoring Dashboard

VII. CONCLUSION

This project presents an effective approach for predictive modeling of engine health using deep neural network ensembles. By integrating real-time sensor data with advanced deep learning techniques, the system is capable of identifying early signs of engine degradation and potential failures. The use of ensemble learning enhances prediction accuracy and robustness by combining the strengths of multiple deep neural network models. The proposed framework supports proactive maintenance, reduces unexpected breakdowns, and improves overall vehicle reliability. Experimental evaluation demonstrates that the ensemble-based approach outperforms individual models in terms of accuracy and consistency, making it suitable for real-world automotive health monitoring applications.

VIII. FUTURE SCOPE

The proposed engine health prediction system can be further enhanced by integrating advanced sensor technologies and higher-frequency data acquisition to capture more detailed engine behavior. Future work may involve incorporating hybrid deep learning architectures that combine convolutional, recurrent, and attention-based models to improve fault detection accuracy. The system can also be extended to estimate the remaining useful life (RUL) of engine components more precisely, enabling predictive maintenance scheduling. Additionally, deploying the model on edge devices can reduce latency and enable real-time decision-making directly within vehicles.

Integration with cloud-based fleet management platforms and digital twin technologies can further support large-scale monitoring and optimization. Finally, the inclusion of explainable AI techniques will improve model transparency and trust, making the system more suitable for safety-critical automotive applications.

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