iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** V **Month of publication:** May 2025

DOI: https://doi.org/10.22214/ijraset.2025.71453

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

Securing Aircraft Maintenance Data with Predictive Insights

Prof. Shilpa T[1], Agam Agarwal[2], Aryan Singh[3], Aryan Dhariwal[4], Prof. Vedasree T K[5], Aayush Prakash[6]
Dept. of IS & E, Bangalore Institute of Technology, Bangalore, India

Abstract: The aviation industry relies on accurate and secure maintenance data to ensure aircraft safety, operational efficiency, and regulatory compliance. Traditional maintenance management systems often face challenges such as data tampering, inefficient record-keeping, and delayed fault detection. This paper proposes an innovative aircraft maintenance system that integrates blockchain technology with machine learning to enhance security, reliability, and predictive capabilities. Blockchain ensures immutability and transparency of maintenance records, preventing unauthorized modifications and enabling trust among stakeholders. Meanwhile, machine learning models analyze real-time sensor data to predict the Remaining Useful Life (RUL) of aircraft components, enabling proactive maintenance scheduling. Smart contracts further automate maintenance validation and alerting, reducing manual intervention and improving workflow efficiency. The proposed system offers a scalable and secure solution that enhances aviation safety, minimizes operational costs, and optimizes aircraft maintenance strategies.

I. INTRODUCTION

Aircraft maintenance is a critical component of aviation safety and operational efficiency. Traditional maintenance management relies heavily on manual record-keeping and scheduled inspections, which can lead to inefficiencies, increased operational costs, and potential safety risks due to delayed fault detection. Furthermore, existing systems often suffer from data integrity issues, where unauthorized modifications or human errors can compromise maintenance logs, leading to compliance violations and operational failures.

To address these challenges, this paper presents an advanced aircraft maintenance system that integrates blockchain technology and machine learning to enhance security, transparency, and predictive capabilities. Blockchain ensures that maintenance records remain immutable and verifiable, preventing tampering and enabling trustworthy data-sharing among stakeholders. Meanwhile, machine learning algorithms analyze real-time sensor data from aircraft engines and components to predict their Remaining Useful Life (RUL), enabling proactive maintenance scheduling and reducing unplanned downtime.

Additionally, smart contracts are employed to automate validation processes, ensuring that predefined maintenance conditions trigger alerts and updates automatically. This reduces reliance on manual intervention, enhances efficiency, and streamlines compliance with aviation regulations. By combining these technologies, the proposed system offers a robust, scalable, and intelligent solution for modern aircraft maintenance management, reducing operational risks and improving overall aircraft performance.

This paper discusses the architecture, implementation, and benefits of the proposed system, highlighting how blockchain and machine learning can revolutionize aircraft maintenance practices.

II. RELATED WORK

A. Litearture Review

The transition from traditional aircraft maintenance record-keeping to blockchain-integrated predictive systems has gained significant attention in recent academic and industry research. Studies highlight the limitations of centralized databases, which are prone to tampering and inefficiencies, leading to increased operational risks. Research suggests that blockchain technology, with its immutable and decentralized structure, enhances traceability and security in aviation maintenance records [1]. The ability of blockchain to ensure real-time data integrity has been emphasized in several studies, demonstrating its effectiveness in preventing unauthorized modifications to critical maintenance logs [2,3].

Predictive maintenance using machine learning models has also been explored extensively. Deep learning techniques, particularly CNN-LSTM architectures, have proven effective in analyzing aircraft sensor data to predict component failures and estimate the Remaining Useful Life (RUL) of engines [6,10]. By leveraging real-time sensor data and historical maintenance records, these models enable proactive maintenance scheduling, reducing unexpected downtime and operational costs.

Additionally, research on hybrid approaches combining blockchain with AI-driven analytics shows promising results in automating maintenance workflows and improving decision-making processes [4,7].

Smart contracts have been proposed as a means to further streamline aircraft maintenance processes. These self-executing contracts, deployed on blockchain networks, can automate maintenance validation and compliance checks. Studies highlight how smart contracts can enforce maintenance schedules, triggering alerts and service requests based on predefined conditions, thereby reducing human intervention and minimizing errors [5,8].

Despite these advancements, challenges remain. Research indicates that integrating blockchain with machine learning requires careful consideration of computational costs and scalability [9]. Furthermore, data privacy concerns and interoperability between various aviation stakeholders continue to be key areas of ongoing investigation.

This study builds upon these findings to develop a robust aircraft maintenance system that integrates blockchain for secure record-keeping and machine learning for predictive maintenance, offering an efficient and scalable solution for modern aviation maintenance management.

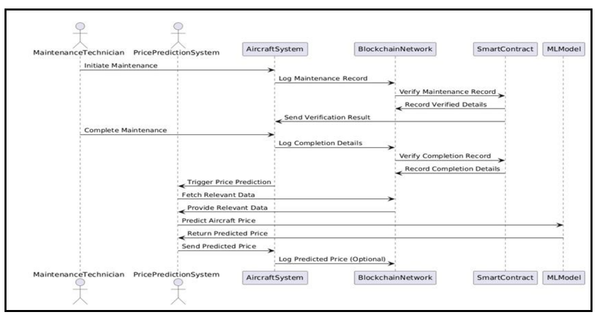
B. Existing Solutions and Limitations

Several automated solutions have been introduced to address the challenges inherent in traditional methodologies. Notable among these are models based on blockchain and machine learning, which have shown significant promise in enhancing data security and predictive accuracy [5], [6]. However, reliance on large, annotated datasets remains a common limitation. Additionally, the integration of blockchain with existing systems and real-time operations can be complex and resource-intensive.

III. SYSTEM DESIGN

A. Sequence Diagram

The sequence for Uploading and Processing maintenance Data is as follows:



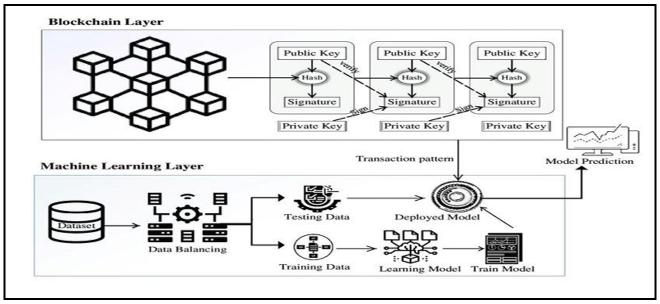
1) *Maintenance Workflow Sequence*

- Maintenance Technician initiates maintenance
- Log Maintenance Record to Aircraft System
- Send Log Maintenance Record to Blockchain Network
- Blockchain Network verifies maintenance record
- Send Verification Result back
- Record Verified Details in Smart Contract and ML Model

2) *Price Prediction Workflow:*

- Maintenance Technician triggers price prediction
- Price Prediction System fetches relevant data
- Provide Relevant Data to Aircraft System
- Predict Aircraft Price
- Return Predicted Price
- Send Predicted Price back to Maintenance Technician
- Optionally Log Predicted Price in systems

B. Architecture Diagram



The diagram illustrates a two-layer architecture integrating blockchain and machine learning technologies:

1) *Blockchain Layer*
- Represents a decentralized network of interconnected blocks
- Uses public and private key cryptography
- Includes signature mechanisms for transaction validation
- Ensures secure and transparent transaction processing

2) *Machine Learning Layer:*
- Starts with a dataset
- Performs data balancing preprocessing
- Splits data into testing and training sets
- Develops learning model
- Trains and deploys machine learning models
- Generates model predictions

IV. IMPLEMENTATION

This section proposes the design, technologies, and architecture for implementing blockchain based aircraft maintenance record storage and predictive insights using LSTM. The following subsections detail the system's modules, data structures, algorithms, and implementation plan.

A. Feature Technology

1) Blockchain Framework: Ethereum-based smart contracts for secure maintenance record storage.
2) Machine Learning Framework: LSTM for predictive analytics and RUL estimation.
3) Flask Web Framework: Web interface for user interaction and data visualization.
4) Ganache: Local blockchain simulator for Ethereum smart contract development and testing.
5) Truffle: Development framework for blockchain-based applications, facilitating contract deployment and testing

B. Major Modules

The proposed aircraft maintenance system consists of five interconnected modules, each designed to facilitate efficient maintenance record management and predictive insights. These modules are described below:

1) Authentication and Authorization Module Ensures secure user access to the system by implementing role-based authentication. This module verifies user credentials and assigns appropriate permissions, preventing unauthorized access to maintenance records and predictive models.
2) Record Storage Module Leverages blockchain to securely store and manage maintenance records. The module ensures data integrity, immutability, and accessibility for authorized stakeholders while preventing tampering or fraudulent modifications.
3) RUL Calculation Module Uses machine learning algorithms to estimate the Remaining Useful Life (RUL) of aircraft components. This module processes sensor data and historical maintenance logs to predict wear and tear, enabling proactive maintenance scheduling.

4) Health Prediction Module Analyzes real-time sensor data from aircraft engines and other critical components to predict potential failures. The module generates alerts based on anomaly detection, allowing maintenance teams to take preventive measures before system failures occur.
5) Smart Contracts Definition Module Implements Ethereum-based smart contracts to automate maintenance processes. This module ensures that predefined maintenance conditions trigger automatic updates, notifications, or service requests, reducing manual intervention and enhancing operational efficiency.

C. Data Structures

The proposed aircraft maintenance system utilizes a structured data model for storing maintenance records and sensor data. This data structure ensures efficient retrieval, security, and integrity through blockchain implementation. The schema is defined as follows:

```
{
    "recordId": "uint",
    "aircraftName": "string",
    "engineId": "uint",
    "sensorValues": [
        "uint", "uint", "uint", "uint",
        "uint", "uint", "uint", "uint"
    ],
    "RUL": "uint"
}
```

D. LSTM Algorithm

1) Step 1: Data Preprocessing

The data preprocessing starts by merging the test dataset (dfTest) with the RUL dataset (dfRUL) based on the unit_id column. The Remaining Useful Life (RUL) is then calculated for each entry by subtracting the current cycles from the maximum cycle value of the corresponding unit, adjusted by the RULmax value from dfRUL. After calculating the RUL, certain sensor columns (s22 and s23) are dropped from both the training and test datasets (df and dfTest) as they are deemed unnecessary or irrelevant for model input. This ensures the data is clean and ready for model training and evaluation.

Example:

```
dfTest=pd.merge(dfTest, dfRUL, on='unit_id')
dfTest['RUL']=(dfTest.groupby(['unit_id'])['cycles'].transform(max)+dfTest['RULmax'])-dfTest['cycles']

df=df.drop(['s22','s23'],axis=1)
dfTest=dfTest.drop(['s22','s23'],axis=1)
```

2) Step 2: Algorithm for LSTM Model Architecture

The LSTM model architecture begins by defining the optimizer as Adam with a learning rate of 0.004. A Sequential model is created, and the first layer is an LSTM with 100 units, using a window of 70 time steps as input and applying L2 regularization to avoid overfitting. This is followed by a second LSTM layer with 50 units, again using L2 regularization. The final layer is a Dense layer with units corresponding to the shape of the labels and a sigmoid activation function to predict binary outputs (RUL classification). The model is compiled with a binary cross-entropy loss function, the Adam optimizer, and recall as the evaluation metric. The model summary is printed to review the architecture.

Example:

```
from tensorflow.keras import regularizers
batch70=70
opt = keras.optimizers.Adam(learning_rate=0.004)
model = Sequential()
model.add(LSTM(input_shape=(batch70,
trainLSTM.shape[2]),units=100,return_sequences=True,activity_regularizer=tf.keras.regularizers.l2(0.01)))
```

```
model.add(LSTM(units=50,return_sequences=False,activity_regularizer=tf.keras.regularizers.l2(0.01)))
model.add(Dense(units=trainLabel.shape[1], activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer=opt, metrics=[tf.keras.metrics.Recall()])
print(model.summary())
```

3) Step3: Algorithm For Model Training

The model training process begins by extracting the unique unit IDs from the training dataset. For each unit, the data is processed in batches of 70 rows. A loop iterates through the training data, selecting windows of 70 consecutive time steps (features), which are appended to the input array. The corresponding labels (RUL values) for each window are also collected. After the data for all units is processed, the input data is reshaped into a 3D array with dimensions suitable for LSTM processing and converted to the float32 data type. The labels are then reshaped into a 2D array for the model. The resulting arrays are ready for training the LSTM model.

Example:

```
batch70=70
trainIDs=list(df['unit_id'].unique())
inputNP = np.empty((0,18), int)
labelList=[]
In [ ]:
# Create 3D array from training set for input to LSTM
for id in trainIDs:
    dfTemp=df.loc[df['unit_id']==id]
    start=0
    for i in  range(len(dfTemp)-batch70+1):
        inputNP = np.append(inputNP, dfTemp.iloc[start:start+batch70,1:-2], axis=0)
        labelList.append(dfTemp['label30'].iloc[start+batch70-1])
        start=start+1
trainLSTM = np.reshape(inputNP, (-1,70, 18))
trainLSTM=trainLSTM.astype('float32')
trainLSTM.shape
In [ ]:
# Array for training labels
trainLabel=np.array(labelList)
trainLabel=np.reshape(trainLabel, (-1,1))
trainLabel.shape
```

4) Step4: Algorithm For Model Evaluation

The model is set to evaluation mode, and the test data is prepared by iterating through each unit ID, extracting relevant features, and reshaping the data into a 3D array suitable for the LSTM model. Once the test data is formatted, it's passed through the trained LSTM model to generate predictions for the Remaining Useful Life (RUL) of each aircraft. These predictions are then compared to the ground truth labels (the actual RUL values). Evaluation metrics such as accuracy or the Dice coefficient are computed to assess the model's performance, and the results are logged for further analysis and refinement of the model.

Example:

```
testIDs=list(dfTest['unit_id'].unique())
inputNP = np.empty((0,18), int)
labelList=[]

for id in testIDs:
    dfTemp=dfTest.loc[dfTest['unit_id']==id]
    start=0
    for i in  range(len(dfTemp)-batch70+1):
```

```
    inputNP = np.append(inputNP, dfTemp.iloc[start:start+batch70,1:-2], axis=0)
    labelList.append(dfTemp['label30'].iloc[start+batch70-1])
    start=start+1
testLSTM = np.reshape(inputNP, (-1,70, 18))
testLSTM=testLSTM.astype('float32')
testLSTM.shape
```

V. TESTING AND EVALUATION

A. Unit Testing

1) Objective: Validate the functionality of individual modules, such as data encryption, blockchain transactions, and machine learning predictions.
2) Approach: Use test scripts to independently test each function, including blockchain-based data storage, encryption methods, and predictive accuracy of machine learning models. Ensure that maintenance records are securely stored and retrieved accurately.
3) Expected Outcome: Each module operates as expected, ensuring data integrity, security, and accurate predictions, while properly handling edge cases (e.g., incomplete or corrupted data).

B. Integration Testing

1) Objective: Ensure smooth interactions between interconnected modules, such as the blockchain framework, machine learning models, and smart contract executions.
2) Approach: Test scenarios like: recording maintenance logs on the blockchain, retrieving stored records, and verifying that machine learning models correctly process sensor data. Ensure that smart contracts trigger appropriate maintenance alerts when necessary.
3) Expected Outcome: The components work together seamlessly, maintaining accurate data storage, retrieval, and predictive insights without errors in communication between blockchain, machine learning models, and smart contracts.

C. Performance Metrics

1) *Response Time*
- Metric: Time taken to preprocess images, run them through the model, and generate segmentation masks.
- Expected Standard: Achieve a response time of under 5 seconds for processing and segmentation to ensure smooth operation for real-time or large-scale data processing.

2) *Scalability:*
- Metric: The system's ability to handle high volumes of seismic image data for salt segmentation.
- Approach: Load testing with large datasets to evaluate the performance of the image processing pipeline and model inference under high load.
- Expected Standard: The system remains responsive and produces accurate segmentation outputs under peak loads, ensuring scalability for processing large sets of seismic images.

VI. RESULTS

While the system is still under development, the expected results from testing and evaluation once the salt segmentation model is operational are:

1) *Enhanced Data Security and Integrity through Blockchain*

By integrating blockchain, aircraft maintenance records are stored in a tamper-proof decentralized ledger. This prevents unauthorized modifications, ensuring that all stakeholders have access to authentic and verifiable data. The immutability of blockchain also helps in regulatory compliance and audit transparency.

2) *Improved Predictive Accuracy for Maintenance Scheduling*

Machine learning models analyze real-time sensor data from aircraft engines to predict potential failures. The system accurately estimates the Remaining Useful Life (RUL) of components, allowing proactive maintenance planning. This reduces the likelihood of sudden failures, improving aircraft safety and operational efficiency.

3) Reduction in Operational Costs and Unplanned Downtime

The predictive maintenance approach significantly minimizes unexpected breakdowns, reducing costly emergency repairs and aircraft groundings. By scheduling maintenance based on data-driven insights rather than routine checks, airlines can optimize resource allocation, leading to lower maintenance costs and increased aircraft availability.

VII. CONCLUSION

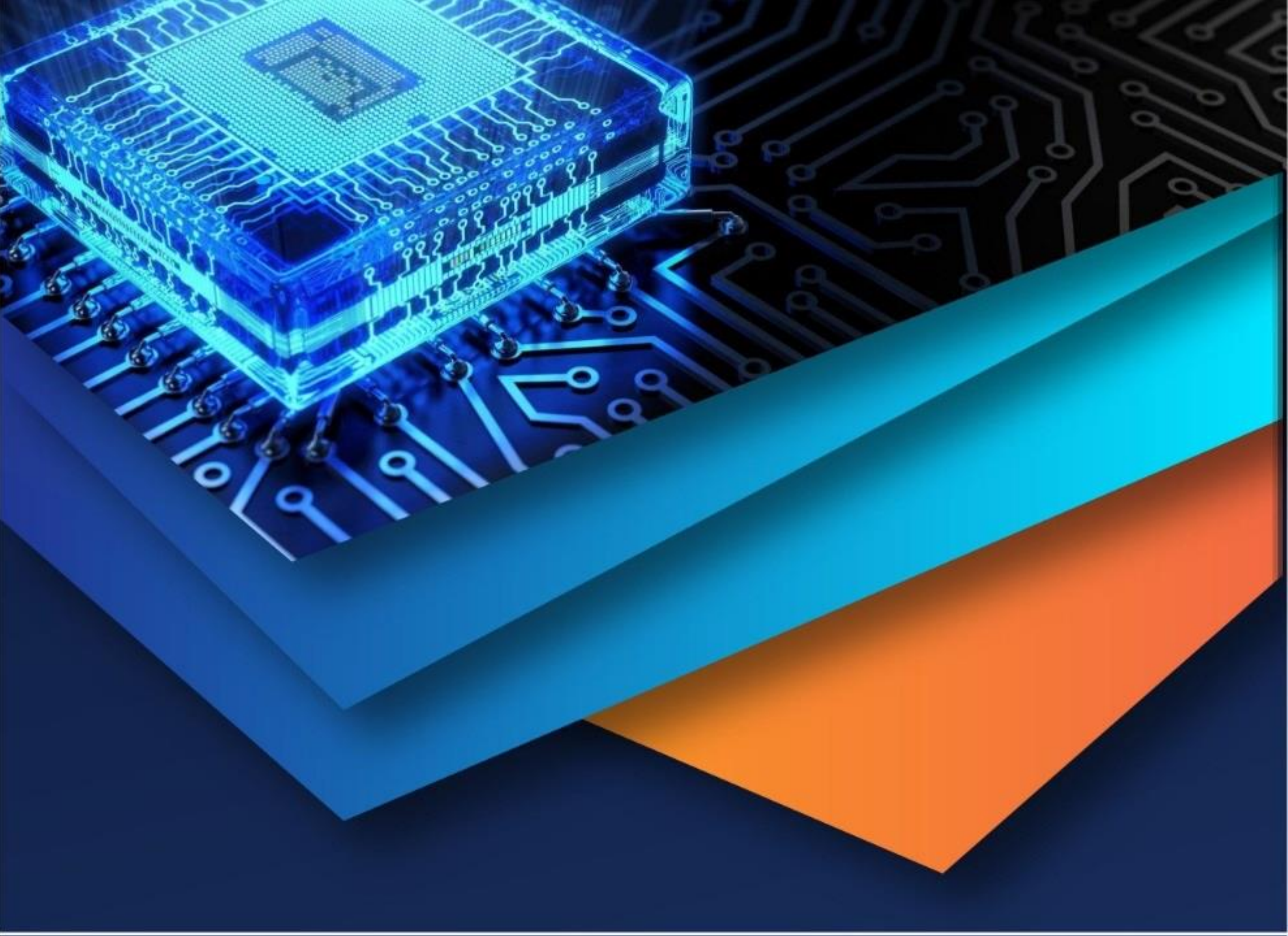
This project demonstrates a robust approach to securing aircraft maintenance data and optimizing maintenance schedules using blockchain and machine learning. By leveraging blockchain technology, maintenance records remain immutable and transparent, reducing the risk of data manipulation and enhancing trust among stakeholders. Meanwhile, machine learning models provide accurate predictions of engine failures, enabling proactive maintenance strategies that minimize unexpected breakdowns and improve operational efficiency. The integration of these technologies significantly improves aviation safety, reduces costs, and ensures regulatory compliance. Future work includes expanding predictive capabilities using deep learning techniques, integrating AI-driven diagnostics for real-time anomaly detection, and enhancing system scalability for deployment across various aircraft models. Furthermore, incorporating more extensive datasets and advanced security mechanisms will enhance the model's accuracy and robustness. This research serves as a foundation for the next generation of intelligent aviation maintenance systems.

VIII.ACKNOWLEDGMENT

We extend our gratitude to Prof. Shilpa T, Assistant Professor, Department of Information Science and Engineering, Bangalore Institute of Technology, for her continuous guidance and support. Her insights and valuable feedback played a crucial role in shaping this research. We would also like to thank Bangalore Institute of Technology for providing the necessary resources and facilities that facilitated the successful completion of this project. Additionally, we appreciate the encouragement and cooperation of our peers and faculty members, whose suggestions helped refine our methodology and improve our findings.
Lastly, we acknowledge our families and friends for their unwavering support, patience, and motivation throughout this research journey.

REFERENCES

[1] Gregorius Airlangga, "Advanced Seismic Data Analysis: Comparative study of Machine Learning and Deep Learning for Data Prediction and Understanding", Research of Artificial Intelligence, Volume 3, Number 2, November 2023.
[2] Muhammad Saif ul Islam, "Using deep learning based methods to classify salt bodies in seismic images", Journal of Applied Geophysics, May 2020.
[3] Jyostna Devi Bodapati, RamaKrishna Sajja, Veeranjaneyulu Naralasetti, "An efficient Approach for Semantic Segmentation of Salt Domes in Seismic Images Using Improved UNET Architecture", Journal of The Institute of Engineers(India), Volume 104, Pages 569-578, April 2023.
[4] Yang Xue, Xiwu Luan, "Implications of Salt Tectonics on Hydrocarbon Ascent in the Eastern Persian Gulf: Insights into the Formation Mechanism of Salt Diapirs, Gas Chimneys, and Their Sedimentary Interactions", Journal of Ocean University of China, July 2024.
[5] Mirnomoy Sarkar, "Salt Detection Using Segmentation of Seismic Image", Journal of A&T State University, March 2022.
[6] Zhifeng Xu, Kewen Li, "3D Salt-net: a method for salt body segmentation in seismic images based on sparse label", Volume 53, pages 29005–29023, 2023.
[7] Yelong Zhao, Bo Liu, "Boundary U-Net: A Segmentation Method to Improve Salt Bodies Identification Accuracy", Conference Paper, January 2022.
[8] Mikhail Karchevskiy, Insaf Ashrapov, Leonid Kozinkin, "Automatic salt deposits segmentation: A deep learning approach", 2018.
[9] Haolin Wang, Lihui Dong, Song Wei, "Improved U-Net-Based Novel Segmentation Algorithm for Underwater Mineral Image", Minzu University of China, Vol.32, No.3, 2022.
[10] Dmitry Koroteev, Zeljko Tekic, "Artificial intelligence in oil and gas upstream: Trends, challenges, and scenarios for the future", Journal on Energy and AI, March 2021.



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY