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Developing a Multivariate Time Series Forecasting Model to Estimate the State of Drone Battery

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Abstract

The decline in battery voltage during unmanned aerial vehicle (UAV) flights poses a critical challenge that can compromise operational safety, reduce flight time, and limit mission efficiency. Battery degradation over time leads to poor motor performance, increases the risk of mid-air failure, and elevates maintenance costs. This study proposes the development of a multivariate time series forecasting model to estimate the state of battery (SoB) of drone batteries, integrating various environmental and operational variables such as velocity, linear acceleration, wind speed, and wind angle. To enhance predictive accuracy, machine learning techniques such as Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Transformer, and Gradient Boosting (GB) are explored. The methodology follows key steps including data collection, Hierarchical Clustering Analysis (HCA) to explore feature relationships, data preprocessing, and model training. The entire prediction system was converted into a web-based interface that allows users to select a model, upload data, and view battery-related results. This approach contributes to the field by improving safety, reducing operational costs, and promoting sustainability in drone applications across delivery, surveillance, and agriculture. The findings are expected to advance battery health monitoring practices and support broader use of predictive analytics in drone operations.

Keywords
Drone Battery, Time Series Forecasting, Unmanned Aerial Vehicle, Deep Learning, Machine Learning.

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1. Introduction

The adoption of drones in various sectors has rapidly expanded in recent years, from commercial delivery to environmental monitoring and agricultural applications. As the use of unmanned aerial vehicles (UAVs) grows, one of the primary concerns remains the limitations imposed by battery life. Drone batteries degrade over time, which directly impacts flight duration, safety, and cost efficiency. This issue is further compounded by environmental conditions and mission-specific variables, making battery performance unpredictable and difficult to manage in real-time.

Current battery management systems primarily rely on threshold-based approaches that fail to dynamically predict State of Battery (SoB). Without accurate SoB estimation, drones are at risk of sudden power failure during flight, which may lead to equipment loss, mission failure, and potential threats to public safety. A reliable SoB prediction model can enable timely maintenance, extend battery lifespan, and optimize drone operation for long-range or time-sensitive missions.

This study addresses the need for a robust and intelligent system that can predict battery state using multivariate time series data. By leveraging machine learning (ML) techniques on real flight data, the project aims to create an adaptive and scalable solution for predictive maintenance and operational safety enhancement.

1.1 Problem Definition

The problem addressed in this study focuses on the lack of predictive battery state monitoring in drone systems. Traditional battery indicators provide insufficient insight into future battery performance, especially under varying environmental conditions. This shortcoming leads to inefficient battery usage, unscheduled downtimes, and a higher probability of in-flight failures.

By predicting the battery state with high precision using data-driven models, this research aims to fill a critical gap in drone operational intelligence. The proposed system allows stakeholders to mitigate risks, reduce costs, and improve sustainability.

1.2 Objectives

The primary objectives of this research are:

- To develop a multivariate time series forecasting model capable of accurately estimating the state of drone batteries.
- To investigate and compare various machine learning techniques such as RNN, LSTM, GB.
- To improve safety, reduce operational costs, and extend battery lifespan in drone applications.
- To enhance battery management to enable drones to fly longer distances and for more extended periods, opening new applications in areas like long-range surveillance, delivery, and agriculture.
- To develop an interactive web-based platform that transforms the predictive models into a user-friendly tool, enabling users to upload data, select a model, and visualize battery performance.

1.2 Symbols and Notations

Symbols and their description is presented in Table 1.

Table1. Symbols and their description

Symbol	Description
SoB	State of Battery
UAV	Unmanned Aerial Vehicle
ML	Machine Learning
LSTM	Long Short-Term Memory
RNN	Recurrent Neural Network
GB	Gradient Boosting
RF	Random Forest
LR	Linear Regression

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2. Literature Review

C.Conte et al. (2022) proposes a data-driven learning-based method aimed at predicting the battery discharge. A segmentation strategy was used to process the data collected from the flight tests. When training the model, an adaptive neural algorithm based on the Bayesian Regularization Backpropagation approach was used. The time-Predictor and the Battery-Discharge-Predictor were developed using a neural network to estimate flight time and current integral. The models were applied in a package delivery mission.

Dragos Alexandru Andrioaia et al. (2024) conducted a comparative study in which they used three machine learning models, Support Vector Machine for Regression (SVMR), Multiple Linear Regression (MLR), and Random Forest (RF) to predict the RUL of Li-ion batteries. For the model's training, the study considers voltage, current, and discharged capacity. The models were validated based on the historical data of the experimental stand developed for studying the degradation process of Li-ion batteries were used. Experimental results show that SVMR and RF have better performance in predicting the RUL.

Jon Ander Martin et al. (2022) performed a comparative analysis of the accuracy and time performance of three types of machine learning models, Support Vector Machine, Relevance Vector Machine, and Fuzzy Inference System to predict the RUL of Li-ion batteries. The study considers the state of discharge, discharge cycle, battery voltage, and for its realization, the datasets made available by the NASA Ames Research Center. From the result obtained by the authors, it is found that both SVR and RVM provide similar results in terms of accuracy, but the computational cost of RVM is lower. As for FIS, it can improve the Mean Absolute Error (MAE) at an intermediate computational cost.

Ashish Khurana and O P Singh. (2024) conducted a comparative study of three types of machine learning models Random Forest Regression (RFR), Extra Tree Regression (ETR), and K-Nearest Neighbors (KNN) to predict the RUL of Li-ion batteries. They considered temperature and time as critical variables. The models are validated using the NASA Lithium-Ion Battery (LIB) dataset. Experimental results show that the Extra Tree Regressor (ETR) model was the most accurate, with a lower error rate and a strong linear correlation.

Makineci Hasan Bilgehan et al. (2022) conducted a comparative study using Artificial Neural Networks (ANN), Adaptive Network Based Fuzzy Inference Systems (ANFIS), and Particle Swarm Optimization-Fuzzy Inference System (PSO-FIS) to predict flight time and battery consumption. In this study, data on GSD, Wind Power, Overlap Rate, FT, and BC were collected by executing flights with the DJI Phantom 4 Pro UAV according to sixty-five photogrammetric flight plans. The results indicate that the ANN model has the highest prediction accuracy, and the lowest error rate compared to the other methods. Rodrigues et al. (2021) proposed an analysis of energy consumption patterns in UAVs using DJI Matrice 100. They collected time-series data via onboard sensors (GPS, IMU, voltage, current) to understand how environmental conditions and payloads affect energy use. Although no predictive model was applied, the study provided valuable insight into energy optimization. However, the data was limited to one drone model and location, which may affect generalizability.

Liu et al. (2024) proposed a hybrid approach for predicting the RUL of lithium-ion batteries by integrating LSTM and XGBoost with the Binary Firefly Algorithm for feature optimization. Using real-world battery datasets, the model achieved high accuracy in estimating degradation. The study recommended adapting this method for UAV applications and testing under real-time conditions.CLDNN + Transformer Study (2022) explored a hybrid neural network to predict battery RUL using CLDNN and Transformer models. The study used lab-based time-series data (charge/discharge cycles, temperature, capacity) and reported improved accuracy compared to traditional models. The authors suggested extending this hybrid approach to UAV applications.

Deep Transfer Learning Study (2023) utilized DTL combined with LSTM to enhance the generalizability of RUL predictions. The study was based on simulated datasets covering voltage, capacity, and cycles. Results showed superior accuracy and robustness over standard methods, but required high computational resources and further testing on UAV systems.

A Data-Driven Framework (2023) developed a hybrid prediction system combining LSTM and XGBoost with a Binary Firefly Algorithm for feature selection. It demonstrated better performance in RUL estimation than single-model techniques. The approach was proposed for drone battery management, though its complexity may require optimization for real-time deployment.

Lukas Blaha et al. (2023) present a technical overview of an automated drone battery management system within a droneport concept. The study proposes a modular infrastructure integrating charging, maintenance, and monitoring systems for UAV batteries. Using sensors, real-time data acquisition, and predictive diagnostics, the system aims to optimize battery lifespan and mission readiness. The paper highlights the role of automation in enhancing UAV reliability and operational efficiency.

Sina Sharif Mansouri et al. (2017) propose a machine learning approach to predict the remaining useful life (RUL) of UAV batteries using flight parameters such as voltage, current, and time. Historical flight data was used to train ML algorithms for accurate life estimation. The results support the use of predictive maintenance to improve mission safety and planning.

Khalifa Jamal Almannaei (2023) investigates the use of machine learning in predictive maintenance for UAV batteries. The study trains supervised models on operational battery data to estimate remaining life and detect potential failures. The research emphasizes the role of predictive analytics in preventing in-flight battery issues and ensuring UAV mission success.

Liyuan Zhang et al. (2022) provide a comprehensive review of ML techniques for lithium-ion batteries, including models for predicting health, capacity, and degradation. The paper discusses challenges such as data quality and model interpretability and suggests that hybrid models combining physical and data-driven methods yield better prediction accuracy.

Kai Luo et al. (2022) review deep learning methods for predicting battery state of health (SOH) and state of charge (SOC). The study evaluates architectures like CNNs and RNNs, showing their effectiveness in handling complex datasets. It emphasizes proper feature selection and preprocessing, noting that deep learning outperforms traditional ML in accuracy and adaptability.

Datong Liu et al. (2013) propose a machine learning-based battery management system (BMS) for UAVs, employing Deep Neural Networks (DNN) to predict the State of Charge (SoC) and Random Forest (RF) for estimating the State of Health (SoH). The system operates under real-time flight conditions and integrates IoT and cloud technologies to improve battery monitoring, reliability, and longevity.

Debabrata Swain et al. (2024) introduce a machine learning model for predicting the Remaining Useful Life (RUL) of electric vehicle batteries using Random Forest and Support Vector Machine. Leveraging NASA datasets, the model incorporates feature selection through One-Way ANOVA and hyperparameter tuning. The study achieved an R^2 score of 0.83 and MSE of 1.67, demonstrating its potential for sustainable battery management.

Zheng Chen et al. (2019) present a hybrid model combining Autoregressive Moving Average (ARMA) and Elman Neural Network (ENN) to estimate the State of Health (SOH) of lithium-ion batteries. The method uses Empirical Mode Decomposition (EMD) and Grey Relational Analysis (GRA) to capture both local fluctuations and long-term degradation. Results show superior accuracy compared to individual models and effective tracking of subtle recovery patterns.

Youdao Wang et al. (2020) offer a comprehensive review of deep learning techniques for RUL prediction of industrial components. The study compares Auto-Encoders, Deep Belief Networks, CNNs, and RNNs in fault diagnostics and degradation forecasting. While highlighting their strengths, the paper notes limited application in RUL tasks and suggests hybrid models to improve accuracy and generalizability.

Khalifa Jamal Almannaei (2023) applies supervised machine learning to forecast battery failures in UAVs using historical usage data. The study demonstrates how predictive analytics can reduce the risk of in-flight power loss, enhancing UAV safety, performance, and mission reliability.

3. Methods

This study follows a structured methodology for developing an intelligent predictive model that estimates the State of the Drone's Battery using multivariate time series data.The dataset used in this study was obtained from a publicly available research article published in Nature Scientific Data (Rodrigues et al., 2021), which contains real-time flight data collected from DJI Matrice 100 quadcopters.The dataset includes the following 21 input variables:

1- Wind Speed	7- Orientation x	13- Velocity z	19- Linear Acceleration x
2-Wind Angle	8- Orientation y	14- Angular x	20- Linear Acceleration y
3-Time	9- Orientation z	15- Angular y	21- Linear Acceleration z
4-Position x	10- Orientation w	16- Angular z	
5-Position y	11- Velocity x	17- Battery Current	
6-Position z	12- Velocity y	18- Battery Voltage	

The methodology involves several sequential steps, covering data handling, feature analysis, model development, and performance evaluation.

3.1 Data Collection

Flight data was collected from drone sensors during actual UAV operations. A total of 279 autonomous flights were recorded, with each flight conducted under varying operational conditions such as altitude, payload, and speed. Additionally, each flight contains a different number of time steps, reflecting the dynamic and variable nature of real-world drone missions.

3.2 Data Preprocessing

Several steps were conducted to prepare the data for analysis, including data cleaning which involves the removal of unnecessary columns only to retain relevant features. and ensuring data integrity by checking for missing values, non-numeric entries, and outliers.

3.3 Feature Selection

Feature selection was conducted using correlation analysis and Hierarchical Clustering Analysis (HCA) to reduce redundancy among input variables and improve model generalization and predicting accuracy, while voltage and current were set as the target variables (Figure 1).

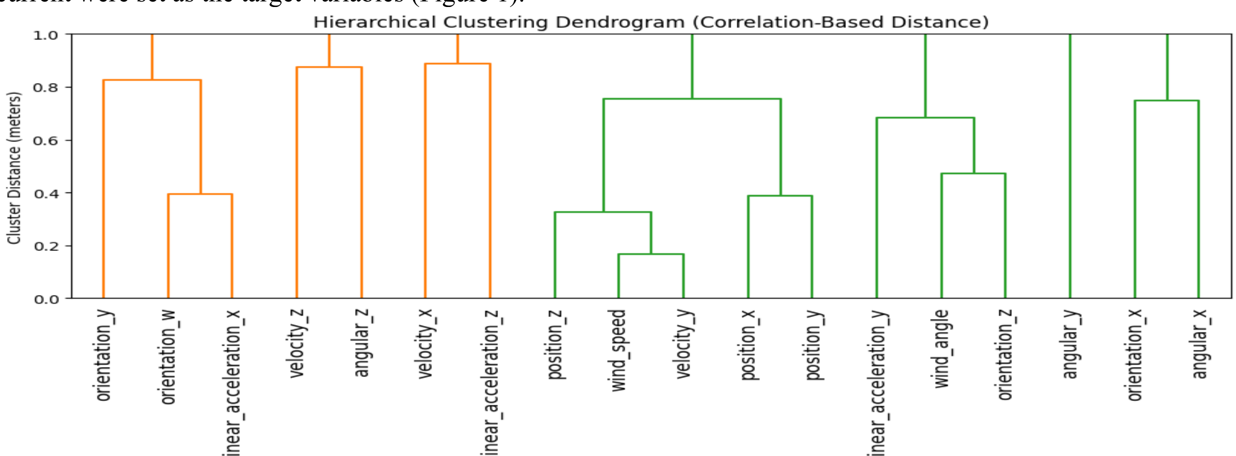

Figure 1. Hierarchical Clustering Dendrogram

Applying Hierarchical Clustering Analysis (HCA) revealed a strong similarity between the variables *wind speed* and *velocity* (Figure 2- Figure 3).

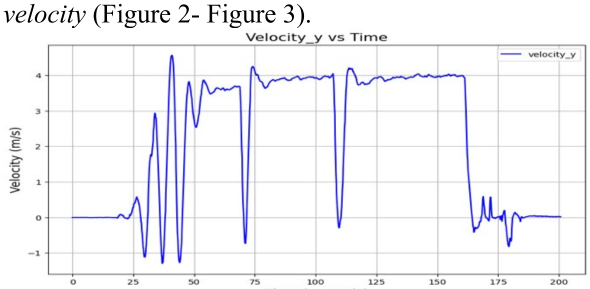

Figure 2. Velocity vs Time

Figure 3. Wind speed vs Time

To further validate this relationship, Change Point Detection was applied using the Pruned Exact Linear Time (PELT) algorithm (Figure 4).

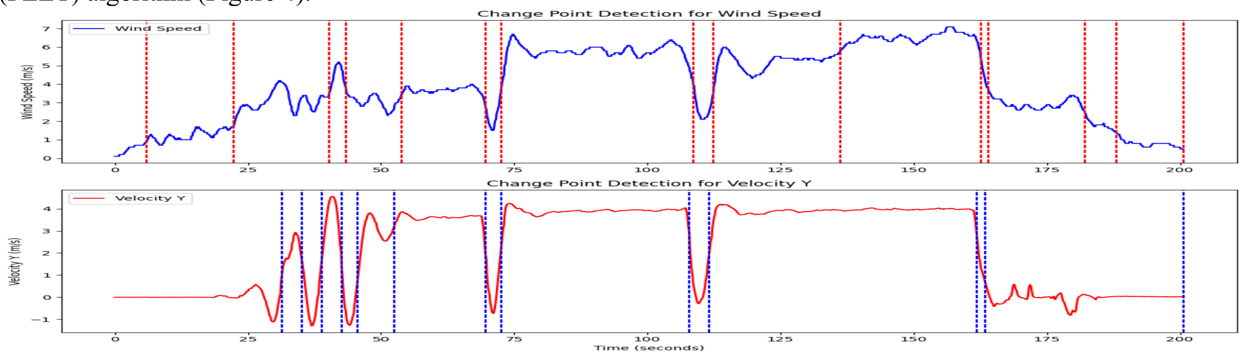

Figure 4. Change point detection

The analysis demonstrated different behavior patterns over time. Based on these findings, the decision was made to retain all variables to capture the full complexity of the data.

3.4 Model Training and Development

Six machine learning models were developed and trained to predict battery state:

- Long Short-Term Memory (LSTM).
- Random Forest (RF).
- Linear Regression.
- Recurrent Neural Network (RNN).
- Transformers.
- Gradient Boosting.

These models have been selected due to their ability to handle multivariate time series data. All models were implemented using Python within the Google Colab environment, and a range of libraries were used throughout the project, such as Pandas, Numpy, Matplotlib, Scipy, Scikit-learn, Tensorflow, Keras, and Ruptures. After predicting the voltage and current using the trained models, the corresponding actual values were calculated. Power was computed by multiplying current and voltage, while energy was derived using trapezoidal numerical integration.

3.5 Model Evaluation

The trained models were evaluated using a set obtained by splitting the dataset with an 80:20 ratio, after applying normalization to ensure consistent scaling. The evaluation relied on several standard regression metrics (Figure 5):

- R-squared (R^2)
- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)

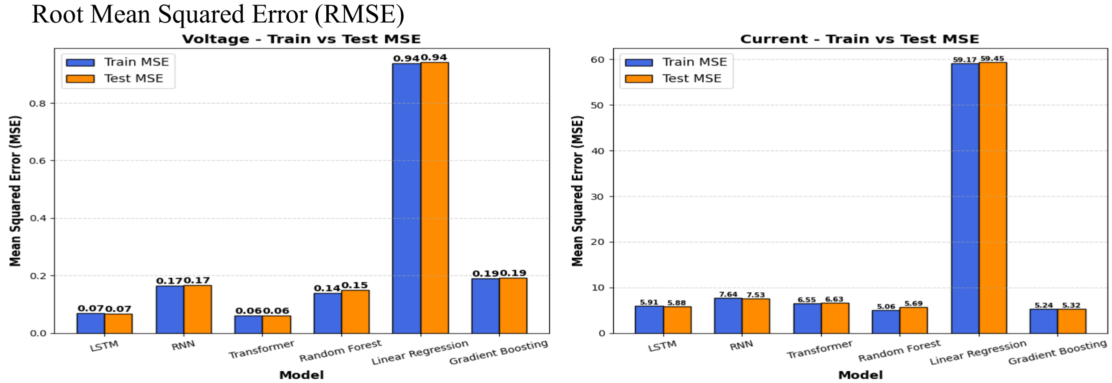

Figure 5. MSE Comparison between models

The following bar charts illustrate the Mean Squared Error (MSE) for training and testing across all models,

- Linear Regression had the highest MSE in both cases, indicating poor fit.

- LSTM, Transformer, and Random Forest achieved lower but balanced MSE values between train and test sets.

4. Results and Discussion

4.1 Models Performance

Six models were tested to evaluate their effectiveness in Predicting the State of the Drone's Battery. Each model was assessed across four output variables: Voltage, Current, Power, and Energy. Performance was measured using R-squared (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) (Table 2).

Table 2. Model Performance results

Model	Variable	AVG: R^2	AVG: RMSE	AVG: MSE	AVG: MAE
RF	Current	0.952	2.3859	5.6926	1.4893
	Voltage	0.8967	0.3862	0.1492	0.2689
	Power	0.9552	50.2365	2523.703	31.1729
	Energy	0.9993	0.2213	0.049	0.1551
LR	Current	0.4991	7.7103	59.4489	6.2665
	Voltage	0.3473	0.9711	0.943	0.7869
	Power	0.5129	165.6605	27443.4	133.2818
	Energy	0.9711	1.4224	2.0232	0.9908
RNN	Current	0.9366	2.7435	7.5269	1.7618
	Voltage	0.8849	0.4078	0.1663	0.3078
	Power	0.9392	58.5201	3424.599	37.2874
	Energy	0.9971	0.4531	0.2053	0.3358
LSTM	Current	0.9504	2.4259	5.8848	1.6173
	Voltage	0.953	0.2607	0.068	0.1903
	Power	0.9523	51.854	2688.833	34.4753
	Energy	0.998	0.3738	0.1397	0.2765
TRANSFORMER	Current	0.9441	2.5752	6.6318	1.6435
	Voltage	0.9581	0.2462	0.0606	0.1791
	Power	0.9459	55.187	3045.605	35.0498
	Energy	0.9969	0.4653	0.2165	0.3421
GB	Current	0.9552	2.3066	5.3205	1.4891
	Voltage	0.8672	0.4381	0.1919	0.3463
	Power	0.9592	47.9704	2301.16	30.4578
	Energy	0.9987	0.3004	0.0902	0.2168

4.2 Discussion

The results show that all the models outperformed Linear Regression, which had the weakest R^2 scores and the highest error margins. Among the models, Random Forest showed strong overall performance, particularly in energy prediction ($R^2 = 0.9993$) and in current ($R^2 = 0.952$), but it was not the top performer across all targets. For voltage prediction, the transformer achieved the highest R^2 score (0.9581), followed closely by LSTM (0.953). For current prediction Gradient Boosting led the performance with the highest R^2 score (0.9552), followed by Random Forest and LSTM. However, Linear Regression significantly underperformed in all categories, confirming its limitations when dealing with time-dependent patterns (Figure 6- Figure 7).

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4.3. Visual Analysis of Individual Flights

Two representative drone flights, Flight 238 and Flight 105, were selected for detailed visual analysis. Each plot compares the actual vs predicted values of the key battery metrics: Voltage, Current, Power, and Energy.

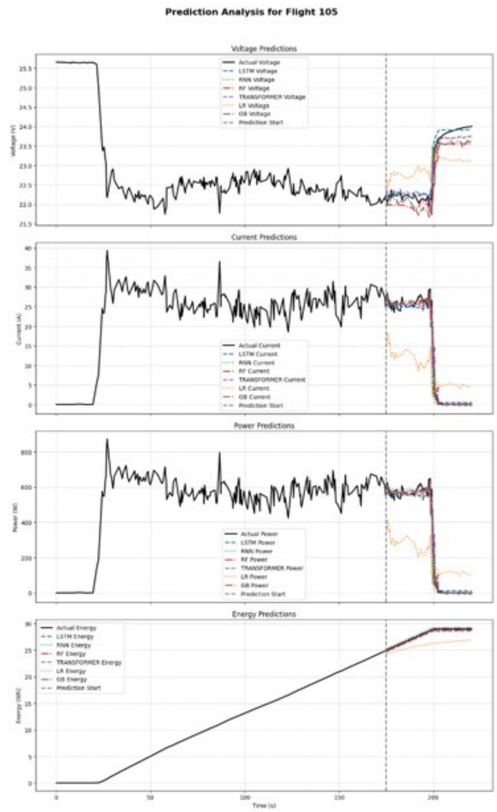

Figure 6. Prediction analysis for flight 105

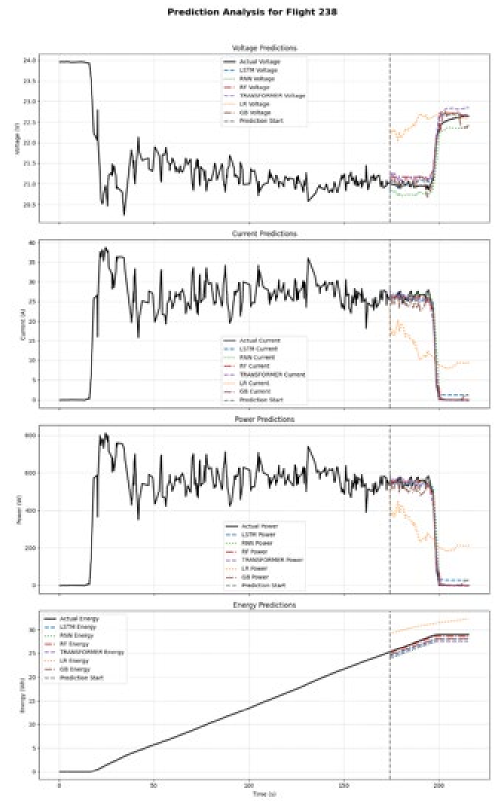

Figure 7. Prediction analysis for flight 238

4.4 Proposed Improvements

To further advance the system beyond its current capabilities, several key improvements are proposed:

- Adopting Alternative Predictive Models: Future versions of the system could integrate a broader range of machine learning and deep learning algorithms, such as Transformer models, Gated Recurrent Units (GRUs), or ensemble learning techniques. These alternatives may offer improved prediction accuracy, better adaptability to various UAV platforms, and enhanced efficiency in handling complex or incomplete datasets.

- Developing an Intelligent Operating System: The existing web tool could be expanded into a comprehensive UAV battery management operating system. This system would interface directly with onboard sensors during live flights, automatically collect and process data, and provide real-time predictions, battery health insights, and safety recommendations without requiring manual data uploads.

- Real-Time Sensor Integration and Automated Decision-Making: By incorporating real-time sensor networks, the system can enable live diagnostics and automated responses. These may include adaptive flight adjustments, early return-to-home commands, and optimized path planning based on ongoing battery assessments.

- System Integration with UAV Control Units: Further development could allow seamless communication between the prediction system and UAV control units, facilitating smart responses such as rerouting, initiating landing protocols, or rescheduling missions when battery levels reach critical thresholds.

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- Cloud-Based Architecture for Scalability: Deploying the system on a cloud infrastructure would enhance scalability, support simultaneous data handling from multiple UAVs, and offer centralized fleet battery monitoring. It would also allow long-term trend analysis and collaborative model training across various users and conditions.

- User Interface Enhancement and Adaptive Feedback: Enhancing the interface with intuitive dashboards, real-time alerts, and graphical analytics can improve user experience. Adding a feedback loop where users can confirm or correct the system's predictions would help refine model accuracy through continuous learning.

These improvements aim to transform the current solution into a smart, autonomous, and scalable system capable of supporting real-time UAV battery management and predictive maintenance across a wide range of operational environments**.**

5. Conclusion

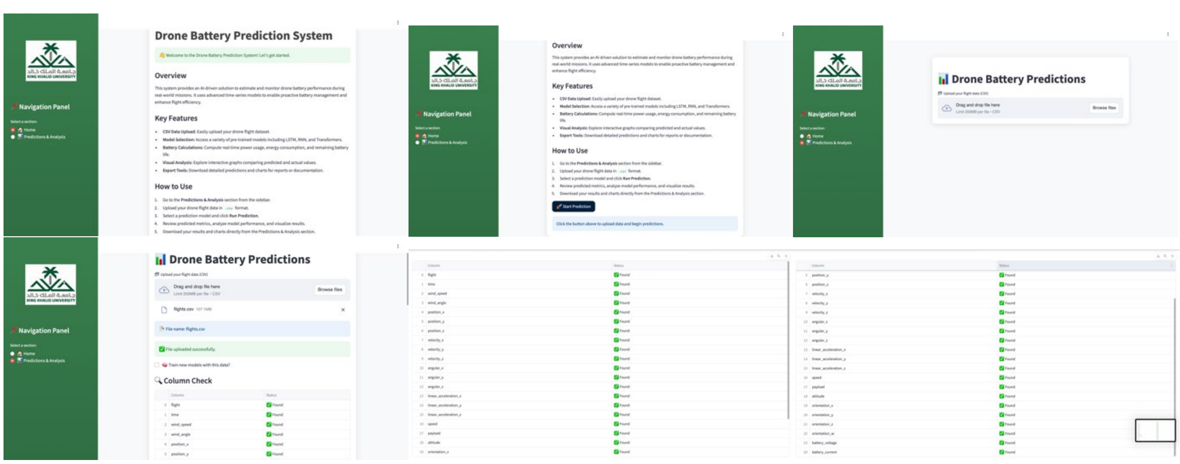
This project successfully developed an AI-powered predictive framework for monitoring and estimating the remaining useful life (RUL) of UAV batteries using multivariate time series data. By analyzing various flight and environmental variables, the framework enhances operational reliability, reduces unexpected failures, and supports proactive maintenance strategies.

Additionally, a web-based tool was created to simplify access to the predictive model. Users with similar input variables can upload their data and instantly receive model predictions through the following link: http://185.223.31.181:8502

Through comparative evaluation, it was found that the Transformer model achieved the highest accuracy in predicting battery voltage, followed by the LSTM model. For current prediction, Gradient Boosting (GB) showed the best performance, followed by Random Forest (RF), and then LSTM. On the other hand, Linear Regression (LR) consistently resulted in the lowest prediction accuracy among all tested models. This contribution offers a practical and accessible solution for supporting data-driven battery diagnostics, contributing to the advancement of UAV operational safety and energy efficiency.

5.1 Web Application Interface To make the system more accessible and user-friendly, we developed a web-based interface that allows users to upload drone flight data, select a machine learning model, and instantly view predictions of battery voltage, current, power, and energy.

Below are screenshots of the developed platform illustrating its main features (Figure 8):



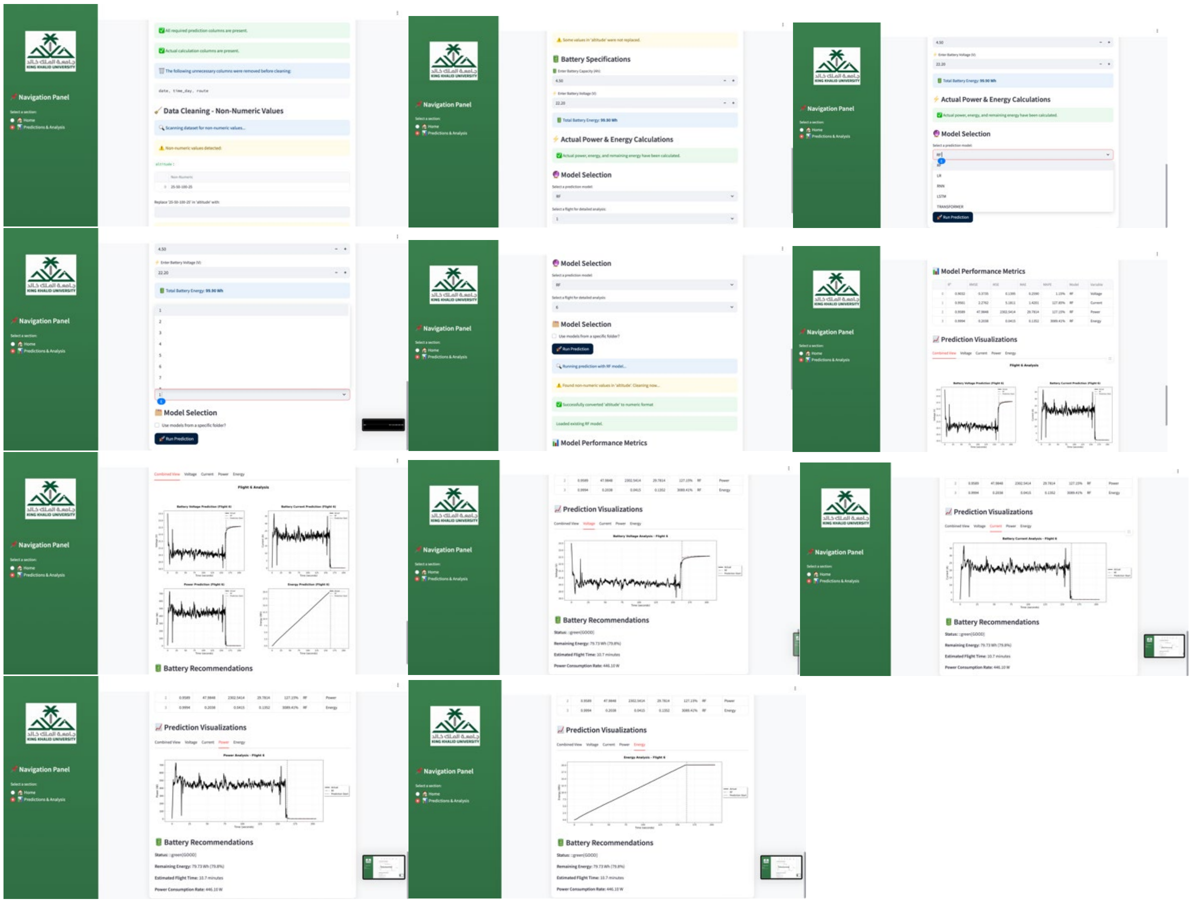


Figure 8. illustrate the main components of the developed web application

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Biographies

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