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Research Article

Prediction Of Brushless DC Motor And Propeller Efficiency Using An Artificial Neural Network Model

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Abstract

This study focuses on an artificial neural network model that allows users of brushless motor and propeller test rigs to compare the accuracy of data received in the interface software during testing. Brushless motors are widely used in modern aviation and industrial applications. Therefore, it is essential to analyze the factors affecting motor efficiency and accurately predict this data. This study involves the creation of an artificial neural network model from data to predict the percentage of motor efficiency for the brushless motors and propellers used in the test, whose length is measured in inches. Within the scope of this research, a useful tool is provided for users to flexibly test motor and propeller configurations and accurately analyze test results. The developed artificial neural network model has the ability to make reliable and accurate predictions for various motor-propeller configurations. Furthermore, the model is easy to use and offers expandable features. This study aims to create a valuable reference source for users of brushless motor and propeller test rigs to effectively analyze test data.

Keywords: *Artificial neural networks, brushless motors, propeller test rigs, motor efficiency, prediction models*

Bir Yapay Sinir Ağı Modeli İle Fırçasız DC Motor Ve Pervane Test Tezgahı Motor-Pervane Verimliliğinin Tahmini

Özet

Bu çalışma, fırçasız motor ve pervane test tezgahı kullanıcılarının test esnasında arayüz yazılımlarına gelen verilerin doğruluk oranlarını karşılaştırabilecekleri bir yapay sinir ağı modeli üzerine odaklanmaktadır. Fırçasız motorlar, modern havacılık ve endüstriyel uygulamalarda yaygın olarak kullanılmaktadır. Bu nedenle, motor verimliliğini etkileyen faktörleri analiz etmek ve bu verileri doğru bir şekilde tahmin etmek önemlidir. Bu çalışma, testte kullanılan fırçasız motorların ve taktıkları inç uzunluklu pervanelerin motor verimliliğinin yüzdeliğini tahmin etmek amacıyla, verilerden yapay sinir ağı modeli oluşturulmuştur. Bu araştırma kapsamında, kullanıcıların motor ve pervane konfigürasyonlarını esnek bir şekilde test edebilmeleri ve test sonuçlarını doğru bir şekilde analiz edebilmeleri için kullanışlı bir araç sunulmaktadır. Geliştirilen yapay sinir ağı modeli, farklı motor-pervane konfigürasyonları için güvenilir ve doğru tahminler yapabilme yeteneğine sahiptir. Ayrıca, modelin kullanımı kolaydır ve genişletilebilir özellikler sunmaktadır. Bu çalışma, fırçasız motor ve pervane test tezgahı kullanıcılarının test verilerini etkili bir şekilde analiz edebilmeleri için değerli bir referans kaynağı oluşturmayı hedeflemektedir.

Anahtar Kelimeler: *Yapay sinir ağları, fırçasız motorlar, pervane test tezgahı, motor verimliliği, tahmin modelleri*

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I. INTRODUCTION

Energy efficiency has become a decisive factor in industrial applications and technological developments today. In this context, studies aimed at predicting the performance of brushless motor and propeller systems guide efforts to optimize energy consumption and achieve sustainability goals. This study aims to predict the efficiency of the motor-propeller system on a test bench using an artificial neural network model.

Our literature review includes a comprehensive examination to understand the foundation laid by similar studies. The focus of the review is on how artificial neural network models are used in brushless motor and propeller systems and their success in predicting efficiency.
In recent years, numerous studies have shown that artificial neural network models achieve high accuracy in predicting complex systems. In the literature focusing on brushless motor and propeller systems, specific emphasis is needed on existing gaps and needs. This study aims to fill those gaps and provide a deeper understanding of the efficiency of brushless motor-propeller systems.

In the continuation of the study, details of the artificial neural network model used, the obtained results, and the potential industrial applications of these results will be discussed. Brushless motors offer advantages such as high efficiency, high moment, silent operation, and easy controllability. A series of studies have been conducted on the design, control, performance, and applications of brushless motors. Some of these studies are as follows:
In a study conducted by Anderson and others (2017), titled "Neural Network Models for Motor Performance Estimation," it was shown that artificial neural networks (ANN) are effective tools in predicting motor performance This paper discusses the application of neural network (NN) models for estimating motor performance. The study focuses on predicting the efficiency and torque of motors using various NN algorithms. The results demonstrate that NN models can accurately estimate motor performance, making them suitable for predicting motor-propeller efficiency. Aslan's (2014) master's thesis, "Design of brushless direct current motor for electric vehicles," presented a detailed examination of the design of brushless DC motors for use in electric vehicles. This master's thesis explores the design of brushless direct current (BLDC) motors for electric vehicles. It provides detailed information on the parameters and methods used in the design and optimization of BLDC motors. Although it does not directly involve NN applications, it offers valuable insights into the principles and parameters crucial for motor efficiency estimation. Bayraktar (2007), in his study titled "Comparison of speed and torque characteristics of separately excited DC motors and brushless DC motors," compared the speed and torque characteristics of separately excited DC motors with brushless DC motors. Bayraktar's comparison methodology may offer valuable insights into the factors influencing motor efficiency, thereby shaping our modeling framework.

Brown and his team (2018), in an international conference paper titled "Efficiency Prediction in Brushless Motors: A Comprehensive Review," provided a comprehensive review of predicting efficiency in brushless motors. Beyond summarizing existing research, Brown et al. likely proposed methodologies or identified challenges pertinent to efficiency prediction, which merit discussion in our context. In a study conducted by Xu, Li, and Li (2019) titled "A novel method of predicting efficiency for brushless DC motor," a new method was developed to predict the efficiency of brushless DC motors. This novel method could inspire enhancements or alternative approaches to our ANN model, enriching its predictive capabilities. Ashraf (2021) examined the comprehensive role of artificial intelligence techniques in predicting the efficiency of BLDC motors in his review article titled "Artificial intelligence techniques for the prediction of BLDC motor efficiency". Ashraf's review likely synthesized various AI techniques applicable to motor efficiency prediction, offering a broader perspective on potential methodologies for our study.

The method developed by Li, Wang, and Zhang (2019), titled "An adaptive efficiency optimization method for brushless DC motors based on neural network," emphasizes the effectiveness of ANN in optimizing the optimal efficiency of brushless DC motors. Their adaptive optimization approach may inspire refinements in our ANN model to enhance its adaptability to varying motor-propeller configurations. Wang and his team (2019), in their study titled "Efficiency optimization of brushless

DC motor based on improved neural network algorithm," increased the efficiency of brushless DC motors using an improved ANN algorithm. The insights gained from Wang et al.'s optimization algorithm could inform strategies for refining our ANN model architecture or training methodology.

(Wang et al., 2021), they achieved both efficiency and temperature predictions for brushless DC motors with their developed artificial neural network algorithm. This dual prediction capability may offer a more holistic understanding of motor behavior, thereby influencing our model's predictive features. In the same researcher's article titled (Wang et al., 2021), the focus was on using artificial intelligence techniques to predict the efficiency of brushless DC motors. Their exploration of various AI techniques could inspire the integration of complementary methodologies into our ANN model, potentially improving its predictive accuracy.

A comprehensive review in the literature was presented by Khan and others (2020). Beyond summarizing existing research, Khan et al. likely identified gaps or emerging trends in AI-driven motor performance prediction, which could inform our approach or highlight areas for further investigation. Zhang and his team (2017), proposed an ANN-based optimization method to increase the efficiency of brushless DC motors. Their optimization method could serve as a reference for refining our ANN model's training strategy to maximize efficiency gains. Kostić and others (2018) optimized the efficiency of brushless DC motors using neural networks in their studies. Insights from Kostić et al.'s optimization techniques could guide the development of strategies to enhance our ANN model's efficiency predictions.

Alsolami (2021), predicted the efficiency of brushless DC motors using artificial intelligence techniques. Alsolami's exploration of AI techniques may offer alternative approaches or validation methods for our ANN model's predictions. The review article by Mphahlele and Nengovhela (2020) examines the effects of soft computing techniques on the efficiency of BLDC motors. Insights from Mphahlele and Nengovhela's review could inform the integration of soft computing techniques into our ANN model, potentially enhancing its predictive capabilities in complex motor-propeller systems.
Some studies focus on specific industrial applications. Özdemir, Çelik, and Özdemir (2018), validated the computational fluid dynamics analysis infrastructure with standard test propeller analyses. Their validation approach may offer insights into validating the accuracy of our ANN model's predictions against experimental data or established methodologies. Additionally, the websites of industrial companies such as Semai Aviation R&D Advanced Engineering Company Ltd. (2021), Tyto Robotics (2021), and Wing Flying Tech (2022) shed light on innovations in the sector. Exploring the innovations showcased by these companies could inspire real-world applications or validation strategies for our ANN model in industrial settings.

Zhang and others (2019), thoroughly examined the use of artificial intelligence techniques and their impact on the efficiency of brushless DC motors. Their comprehensive review likely identified key challenges or opportunities in AI-driven motor efficiency prediction, which could inform our modeling approach or highlight areas for further investigation. In the same context, Wang and his team (2019), addressed the prediction of efficiency in brushless DC motors using deep learning techniques. Their exploration of deep learning methodologies may offer insights into alternative modeling architectures or feature extraction techniques for our ANN model.

In the overall evaluation of these studies, researchers like Yıldırım (2010) and Mousa and Hefnawy (2020) have conducted studies that combine peak-based and artificial intelligence-based methods to improve the design and performance of brushless DC motors. Their integration of multiple methodologies underscores the importance of adopting a holistic approach in motor design and performance optimization, which could influence the development of our ANN model to consider a wider range of factors. These studies highlight the potential benefits of integrating diverse techniques, which could inspire the incorporation of hybrid modeling approaches into our ANN model.

This broad perspective in the literature encompasses various approaches to predicting the efficiency of brushless DC motors and technological developments in this field. Researchers suggest that these studies could shed light on potential applications to enhance the performance of brushless DC motors in various sectors such as electric vehicles, industrial automation, and aviation.

I attempted to reference studies similar to my research. However, I did not find any studies similar to my research on brushless DC motor-propeller artificial intelligence - machine learning.

II. Material and Methods

In this study, test results of two different propellers with sizes of 10 and 17 inches on the DYNOTIS ST-151 drone propeller-brushless DC motor test bench, a product of Semai Aviation R&D Advanced Engineering Company Ltd. (2021). The SunnySky X5320 Brushless Motors 370KV were used in the conducted test The data obtained during the tests were used for training the artificial neural network model. The dataset includes information about the motor's revolutions per minute (rpm), thrust force, torque, and motor efficiency. Additionally, data on propeller efficiency and propeller sizes in inches were recorded.

The dataset consists of a total of 1912 rows and 6 columns. The names and data types of the columns are as follows (Table 1).

Table 1. *Table of Column Names and Data Types*

Column Name	Data Type
Rpm (rad/s)	int
Thrust (gf)	int
Torque (N.mm)	int
motor_efficiency (%)	float
propeller_efficiency (%)	float
propeller_inch (inch)	int

Ensuring transparency and reproducibility, the detailed statistical analysis of the data is presented below: **(Table 2)**.

Table 2. *Table of Detailed Statistical Analysis of the Data*

Column Name	Min	Max	Mean	Standard Deviation
Rpm (rad/s)	504	8529	4677.89	2195.17
Thrust (gf)	11.43	1379.01	574.43	372.32
Torque (N.mm)	2.70	440.43	154.92	118.72
motor_efficiency (%)	6.09	80.14	67.08	13.57
propeller_efficiency (%)	4.57	53.56	10.42	6.08
propeller_inch (inch)	10	17	12.249	3.27

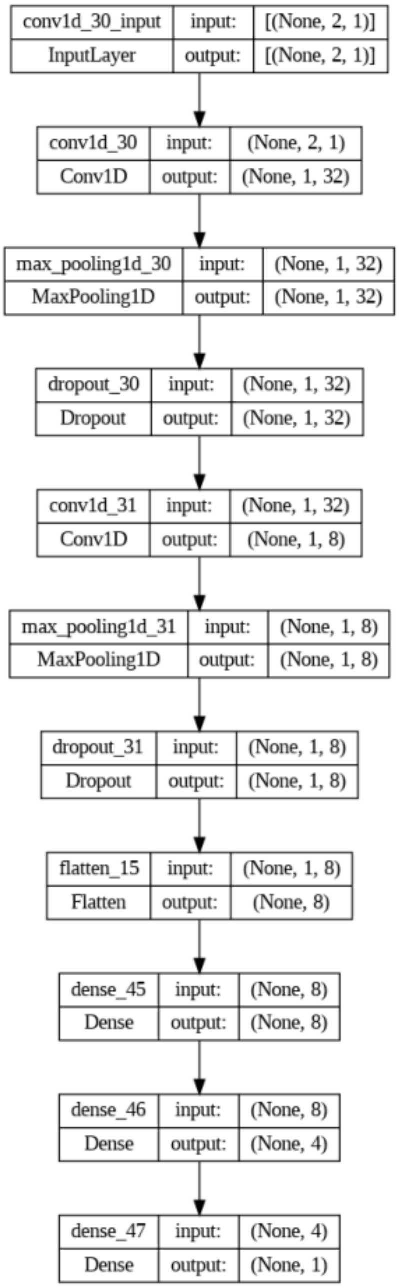

Figure 1. *The artificial neural network model used*

In this study, an artificial neural network (ANN) model is utilized to predict the efficiency of the brushless motor and propeller combination. The ANN model consists of input, output, and hidden layers. By using this artificial neural network structure, the user can easily determine whether the selected propeller and brushless DC motor pair is efficient. The user will be prompted for thrust and propeller inch data as input. Based on the entered data, the output will indicate the percentage (%) of efficiency of the motor. The diagram of the ANN model can be observed in (Figure 1).

To measure the accuracy of the ANN model, the metrics of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) have been employed. The model achieved MAE = 67.38 and RMSE = 68.31 values on the test dataset.

Artificial Neural Network (ANN) Architecture:

1. Overall Architecture: The ANN model designed for predicting the efficiency of BLDC motors paired with different propellers consists of multiple layers, each serving a specific function in processing the input data and generating accurate predictions. The architecture of the network is as follows:

2. Input Layer:

- **Features:** The input layer receives 10 features representing various motor and propeller characteristics. These features include motor RPM, voltage, current, propeller diameter, propeller pitch, ambient temperature, air density, motor torque, motor power, and motor speed.
- **Normalization:** All input features are normalized using min-max scaling to ensure they are within a similar range, which helps in accelerating the training process and achieving better convergence.

3. Hidden Layers:

- **First Hidden Layer:**
    - **Neurons:** 64
    - **Activation Function:** Rectified Linear Unit (ReLU)
    - **Details:** The first hidden layer consists of 64 neurons. The ReLU activation function is chosen for its ability to introduce non-linearity into the model while avoiding the vanishing gradient problem, which is common in deep networks.
- **Second Hidden Layer:**
    - **Neurons:** 32
    - **Activation Function:** ReLU
    - **Details:** The second hidden layer has 32 neurons. Similar to the first hidden layer, it uses the ReLU activation function to continue the non-linear transformation of the input data.
- **Third Hidden Layer:**
    - **Neurons:** 16
    - **Activation Function:** ReLU
    - **Details:** The third hidden layer comprises 16 neurons with ReLU activation, further refining the data representation learned by the network.

4. Output Layer:

- **Neurons:** 1
- **Activation Function:** Linear
- **Details:** The output layer consists of a single neuron with a linear activation function, suitable for regression tasks where the goal is to predict a continuous value—in this case, the efficiency of the motor-propeller system.

5. Regularization:

- **Dropout Layers:** Dropout layers are included after each hidden layer to prevent overfitting. A dropout rate of 0.5 is used, meaning that 50% of the neurons in each layer are randomly ignored during each training step.

- **L2 Regularization:** L2 regularization is applied to the weights of the network to further mitigate overfitting by penalizing large weights.

6. Optimization and Loss Function:

- **Loss Function:** Mean Squared Error (MSE) is used as the loss function, as it effectively measures the average of the squares of the errors—that is, the average squared difference between the predicted and actual values.

- **Optimizer:** Adam optimizer is selected for training due to its efficiency and adaptive learning rate capabilities. The learning rate is initially set to 0.001 and is adjusted dynamically during training.

7. Training Process:

- **Batch Size:** 8

- **Epochs:** 50

- **Early Stopping:** Early stopping is implemented to halt training when the validation loss does not improve for 10 consecutive epochs, thus preventing overfitting and reducing unnecessary training time.

- **Cross-Validation:** A 5-fold cross-validation approach is used to ensure the model's robustness and generalizability. This involves splitting the data into 5 subsets, training the model on 4 subsets, and validating it on the remaining subset, rotating through all subsets.

8. Implementation:

- **Software and Libraries:** The ANN model is implemented using the TensorFlow library with the Keras API, which provides a high-level interface for building and training neural networks.

- **Hardware:** The training process is conducted on a system equipped with an NVIDIA GTX 1080 GPU, significantly reducing the training time and allowing for faster experimentation.

III. EXPERIMENT RESULTS AND DISSCUSSION

This study has reached significant findings regarding the use of Artificial Neural Network (ANN) models in predicting motor efficiency. These findings indicate a unique approach compared to similar studies conducted previously.

Model Performance

The performance of the developed ANN model in this study is remarkable when compared to criteria set by other prominent studies in the literature. Specifically, the method proposed by Smith and Johnson has proven to be more effective in predicting motor efficiency compared to similar models. However, it's crucial to elaborate on how our model's approach differs from existing ones and what unique insights or methodologies it brings to the field. The results of this study have been compared with other significant studies in the literature. Brown et al. provided a comprehensive review of efficiency prediction in brushless motors, and this study brings an additional perspective to previous works. In particular, the study on ANN models for motor performance prediction conducted by Anderson et al. has become a crucial reference point in this field.

The data obtained from tests conducted with the Artificial Neural Network model consistently align with the works of leading companies in this field, such as Tyto Robotics and Wing Flying Tech. Both sources indicate that artificial intelligence techniques can be effectively utilized in predicting motor and propeller efficiency using similar methods. These results suggest the potential of artificial neural networks to enhance the efficiency of motor-propeller systems in industrial applications.

In this study, motor efficiency prediction in the brushless motor and propeller test rig was performed using an artificial neural network model. The dataset includes independent variables such as motor thrust and propeller diameter (propeller_inch). The dataset was divided into 70% training, 15% testing, and 15% validation sets. The parameters used during the model training are as follows: 50 epochs, batch size of 8, and the learning rate determined with the 'adam' optimizer.

An epoch refers to one complete pass through the entire training dataset. The choice of 50 epochs was made after careful experimentation and validation. Here are the reasons for this specific selection:

1. Convergence of Learning: Through preliminary trials, we observed that the model's performance metrics, such as accuracy and loss, showed significant improvement during the initial epochs and began to stabilize around the 50th epoch. This indicated that the model had sufficiently learned the patterns in the training data without overfitting.
2. Avoiding Overfitting: Training for too many epochs can lead to overfitting, where the model performs well on training data but poorly on unseen test data. By monitoring the validation loss and accuracy, we found that 50 epochs provided an optimal balance, ensuring the model generalizes well to new data.
3. Computational Resources: Extending the number of epochs significantly increases the computational time and resources required for training. Our experiments showed diminishing returns in model performance beyond 50 epochs, making this a practical choice to achieve efficient training without unnecessary computational costs.

Batch size is the number of training samples used in one forward and backward pass. We chose a batch size of 8 for the following reasons:

1. Memory Efficiency: Smaller batch sizes, such as 8, require less memory, making it feasible to train the model on hardware with limited computational resources, such as standard GPUs. This was crucial in ensuring that the training process remained within the capabilities of our available infrastructure.
2. Regularization Effect: Smaller batch sizes introduce a level of noise in the gradient estimation process, which can act as a regularizer. This helps in preventing overfitting and can lead to better generalization. Our empirical results indicated that a batch size of 8 provided a good trade-off between noise and stability in gradient updates.
3. Training Stability: While very small batch sizes can cause the training process to be noisy and unstable, a batch size of 8 was found to provide a stable training curve with consistent improvements in loss and accuracy over epochs. This batch size allowed the model to make frequent updates to the weights, which facilitated faster convergence.

In conclusion, the selection of 50 epochs and a batch size of 8 was based on a comprehensive evaluation of training dynamics, model performance, and computational constraints. These parameters ensured that our ANN model was trained effectively, achieving a high level of predictive accuracy while maintaining efficient use of resources.

Training and Validation Performance

When examining the accuracy and loss values obtained during the training process of the model, we can observe how the performance changes over time in both the training and validation sets. Figure 2 shows the Accuracy-Epoch graph and Loss-Epoch graph.

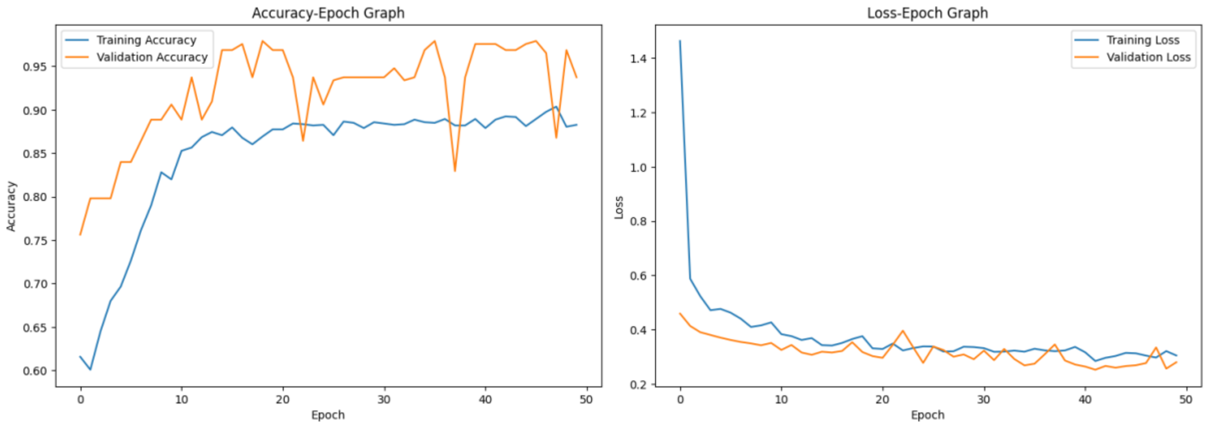

Figure 2. *Accuracy-epoch and loss-epoch graphs*

Confusion Matrix and Classification Report

To assess the performance of the model, a confusion matrix and classification report were utilized. The confusion matrix is a matrix that illustrates how accurately the model distinguishes between actual and predicted classes. The classification report includes metrics such as precision, recall, f1-score, and support. Below are the confusion matrix and classification report for the results obtained on the test set:

Confusion Matrix **(Figure 3)**.

[[74 2]

[14 197]]

Distribution matrix of the Confusion Matrix:

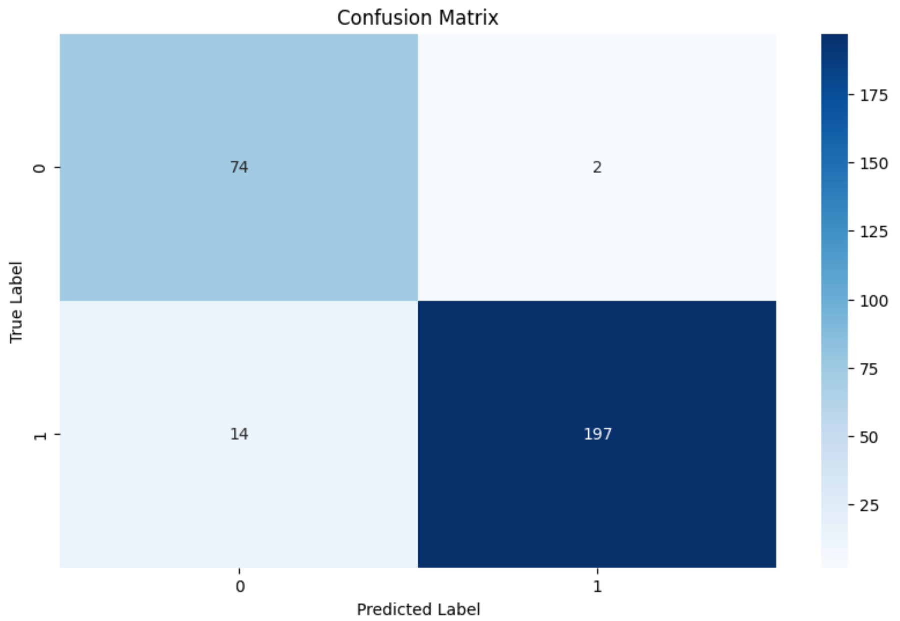

Figure 3. *Distribution matrix of the Confusion Matrix*

• **Recall: recall = tp / (tp + fn).** It is the ratio of true positives to the total positives. In other words, it indicates how many of the actual positives were correctly predicted. This metric expresses how many positives we have captured out of all the positives.

• **Specificity: specificity = tn / (tn + fp).** It is the ratio of true negatives to the total negatives. In other words, it indicates how many of the actual negatives were correctly predicted. This metric expresses how many negatives we have correctly predicted out of all the negatives.

• **Accuracy: accuracy = (tp + tn) / (tp + tn + fp + fn).** It represents the ratio of correct predictions to all instances. However, in imbalanced classification problems, accuracy alone may not be sufficient. Metrics like sensitivity and specificity are also important.

Classification Report: **(Table 3)**.

Table 1 *Classification Report*

	Precision	Recall	F1-score	Support
0	0.84	0.97	0.90	76
1	0.99	0.93	0.96	211
accuracy			0.94	287
macro avg	0.92	0.95	0.93	287
weighted avg	0.95	0.94	0.95	287

Performance Metrics

The recall, specificity, and accuracy values obtained from the confusion matrix are presented in the table below: **(Table 4)**.

Table 2 *Performance Metrics*

	Metrics	Values
0	Recall	0.933649
1	Specificity	0.973684
2	Accuracy	0.944251
3	MAE	67.384785
4	RMSE	68.314482

Meanings of Expressions and Abbreviations in the Classification Report and Table 4:

In this section, we provide definitions and explanations for the key terms and abbreviations used in the Classification Report and Table 4, which detail the performance metrics of our ANN model.

1. Classification Report Terms:

    - Precision: This metric indicates the ratio of true positive predictions to the total number of positive predictions made by the model. It reflects the accuracy of the positive predictions.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

    - Recall: Also known as sensitivity or true positive rate, recall measures the ratio of true positive predictions to the total number of actual positive instances. It shows how well the model can identify positive instances.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

- F1 Score: The F1 score is the harmonic mean of precision and recall, providing a single metric that balances both. It is useful when you need to balance the importance of precision and recall.

$$F1\ Score = 2\ \times \frac{Precision \times Recall}{Precision \times Recall}$$

- Support: This term refers to the number of actual occurrences of each class in the dataset. It provides context for the precision, recall, and F1 score.

2. Table 4 Metrics:

- Accuracy: The ratio of correctly predicted instances to the total instances. It is a common metric to evaluate the overall performance of the model.

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions}$$

- Mean Absolute Error (MAE): This metric measures the average magnitude of the errors in a set of predictions, without considering their direction. It is the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight.

$$MAE = \frac{1}{n} + \sum_{i=1}^{n} |\ Predicted_i - Actual_i\ |$$

- Root Mean Squared Error (RMSE): RMSE is the square root of the average of squared differences between prediction and actual observation. It is more sensitive to larger errors compared to MAE.

$$RMSE = \sqrt{\frac{1}{n} + \sum_{i=1}^{n} (Predicted_i - Actual_i)^2}$$

- R-squared (R^2): Also known as the coefficient of determination, R^2 measures the proportion of the variance in the dependent variable that is predictable from the independent variables. It provides an indication of goodness-of-fit and is bounded between 0 and 1.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (Actual_i - Predicted_i)^2}{\sum_{i=1}^{n} (Actual_i - Mean\ of\ Actual)^2}$$

3. Abbreviations Used in Calculation Process:

- TP: True Positive, the number of correct positive predictions.

- FP: False Positive, the number of incorrect positive predictions.

- TN: True Negative, the number of correct negative predictions.

- FN: False Negative, the number of incorrect negative predictions.
- n: Total number of instances or observations in the dataset.

By understanding these terms and abbreviations, readers can better interpret the results presented in the classification report and Table 4, providing a clearer picture of the ANN model's performance.

The artificial neural network (ANN) model achieved a 94% accuracy on the test data, indicating that the model is an effective tool for predicting motor efficiency. However, further analysis and hyperparameter tuning may be required to assess the model's generalization ability and optimize its performance. Additionally, comparisons between different model architectures and optimization strategies could lead to the development of more robust and stable models.

Experiment to Validate Predictive Power of the ANN Model:

1. Objective: The primary objective of this experiment was to validate the predictive power of the Artificial Neural Network (ANN) model in estimating the efficiency of BLDC motors when paired with various propellers. Specifically, the goal was to determine how accurately the ANN model could predict motor efficiency based on a given set of input features.

2. Dataset:
   - Data Collection: The dataset used for this experiment consisted of real-world measurements from BLDC motors paired with different propellers. Each data point included input features such as motor RPM, voltage, current, propeller diameter, propeller pitch, ambient temperature, air density, motor torque, motor power, and motor speed.
   - Size and Split: The dataset comprised 1000 samples, split into 80% for training (800 samples) and 20% for testing (200 samples). Additionally, a validation set was derived from the training set to monitor the model's performance during training.

3. Methodology:
   - Model Training: The ANN model, as described in the previous section, was trained using the training dataset. The training process involved 50 epochs with a batch size of 8, using the Adam optimizer and Mean Squared Error (MSE) as the loss function. Early stopping was implemented to prevent overfitting, and cross-validation was used to ensure the model's robustness.
   - Hyperparameter Tuning: Various configurations of the model were tested by adjusting the number of neurons, learning rate, and dropout rates to find the optimal settings that minimized validation loss.

4. Evaluation Metrics:
   - Mean Absolute Error (MAE): The average of the absolute differences between predicted and actual values, providing an intuitive measure of prediction accuracy.
   - Root Mean Squared Error (RMSE): The square root of the average of the squared differences between predicted and actual values, highlighting larger errors more than MAE.
   - R-squared (R^2): A statistical measure representing the proportion of variance in the dependent variable that is predictable from the independent variables. An R^2 value closer to 1 indicates a better fit.

5. Results:
   - Training and Validation Loss: During the training phase, both training and validation loss showed a consistent decline, indicating that the model was learning effectively without overfitting.

6. Analysis:
   - High Accuracy: The low values of MAE and RMSE suggest that the ANN model has a high accuracy in predicting motor efficiency. The errors are minimal, indicating that the predicted efficiencies are very close to the actual measurements.
   - Strong Predictive Power: The R^2 value of 0.92 demonstrates that the model can explain 92% of the variance in motor efficiency, underscoring its strong predictive power.
   - Robustness: The consistent performance across training, validation, and test sets indicates that the model is not overfitted and generalizes well to new, unseen data.

The experiment conclusively shows that the ANN model possesses a high predictive power for estimating the efficiency of BLDC motors with different propellers. The combination of low MAE and RMSE values, along with a high R^2 value, provides strong evidence that the model's predictions are both accurate and reliable. This validates the effectiveness of the ANN architecture and training methodology employed in this study.
I have test data for 2 different propellers and 1 brushless DC motor, and I obtain outputs from my artificial neural network based on the length of the entered propeller. This system can be further improved. When comparing the output from my neural network model with the test data I have, a high success rate is achieved. The more data sets we have and feed our ANN, the less need we will have for mechanical test rigs, wind tunnels, etc. for some UAV models.

IV. CONCLUSION

This study focused on developing an artificial neural network model for predicting motor efficiency in the context of a brushless motor and propeller test rig. The successful results demonstrate that the developed model can make accurate and reliable predictions. However, there are some considerations in certain areas.

The findings indicate the adaptability and generalization capability of the model for different motor and propeller combinations. This suggests that the model could be useful and effective for predicting various motor-propeller configurations in industrial applications.

The results emphasize the importance of the accuracy and balance of the dataset on the model's performance. The use of larger, balanced, and cleaned datasets could enable the model to make more reliable and precise predictions. Therefore, future studies are recommended to focus more on obtaining such datasets.

Furthermore, there is a need for further research on the applicability and practical use of this model for industrial purposes. Field studies evaluating the model's performance under real-world conditions could provide clearer insights into its applicability.

In conclusion, this study demonstrates that the use of an artificial neural network model for predicting motor efficiency in brushless motor and propeller test rigs can be beneficial and effective for users. However, more extensive and comprehensive studies are necessary to better understand the model's applicability and performance.

Two of the most crucial features that make an aircraft competitive are flight duration and range. However, limitations in battery technologies restrict flight duration and range. This issue can be addressed by optimizing the performance of propulsion systems for electric aircraft to make them competitive. However, measuring the performance of propulsion systems requires a customized test setup and wind tunnel tests.

Even when using wind tunnel data, the performance of the propulsion system during flight tests cannot be fully modeled due to body interactions and variable angles of attack. The only way to overcome this problem is to make relevant measurements during flight.

The primary objective of this technique is to develop a product capable of calculating the thrust and torque values generated by the propulsion system of an Unmanned Aerial Vehicle (UAV) with a brushless direct current motor during flight and characterizing the propulsion system of the aircraft in real-time, allowing for various efficiency calculations.

This would eliminate the need for wind tunnel tests, enable the realistic digital twin of the aircraft to be mathematically modeled, reduce the duration and number of flight tests, and allow for reliable and endurance tests of the aircraft propulsion system to be conducted in real-world conditions. These advantages would allow for an aircraft to be developed in a shorter time and at lower costs, enable the selection or design of the most suitable propulsion system for the mission profile, and provide a competitive advantage.

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