LAB 2 – Plain Ol' HTML

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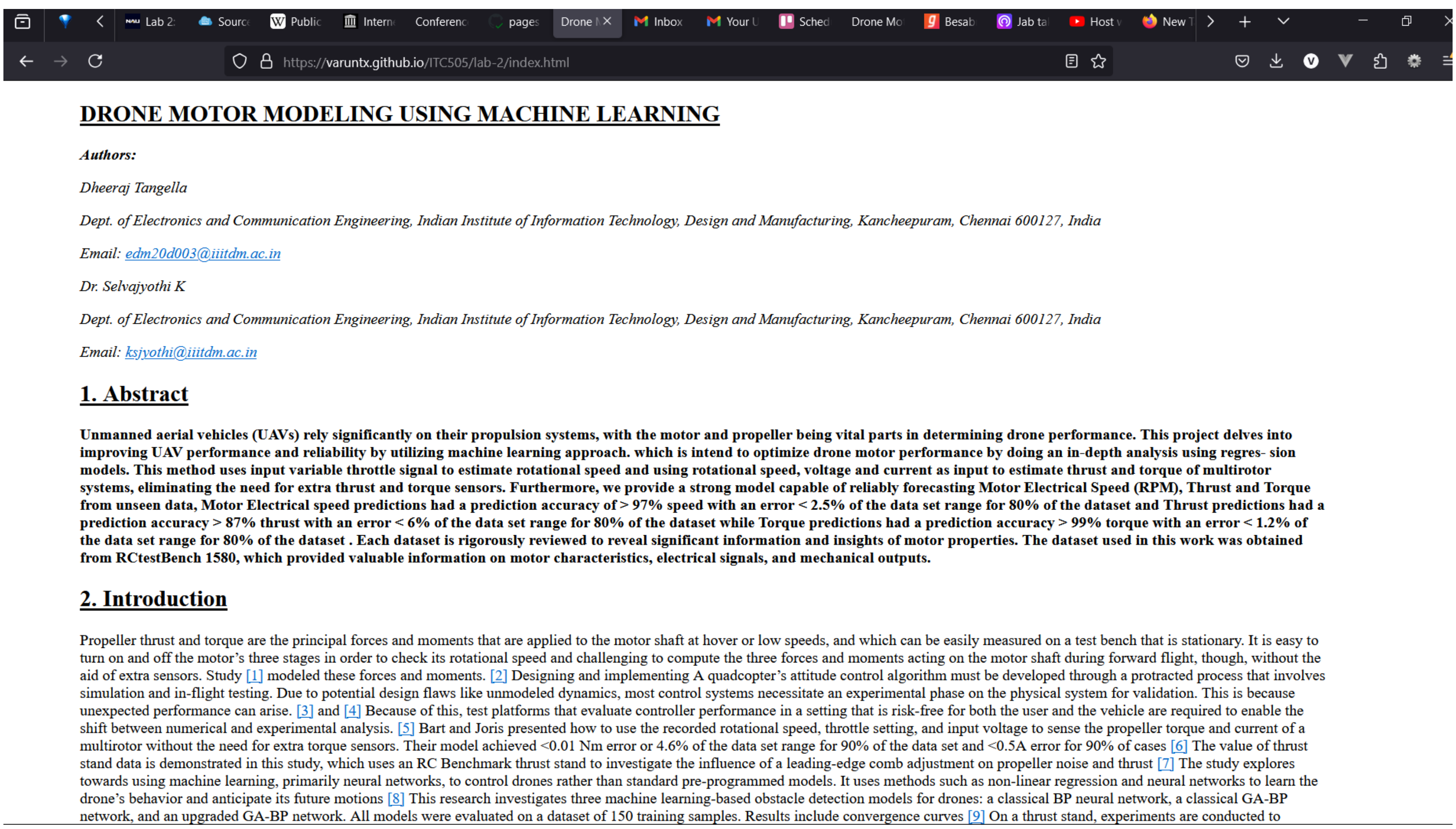
1. Working URL of the Web page: https://varuntx.github.io/ITC505/lab-2/index.html

2. Screenshots of the working page:



DRONE MOTOR MODELING USING MACHINE LEARNING

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1. Abstract

Unmanned aerial vehicles (UAVs) rely significantly on their propulsion systems, with the motor and propeller being vital parts in determining drone performance. This project delves into improving UAV performance and reliability by utilizing machine learning approach. which is intend to optimize drone motor performance by doing an in-depth analysis using regres- sion models. This method uses input variable throttle signal to estimate rotational speed and using rotational speed, voltage and current as input to estimate thrust and torque of multirotor systems, eliminating the need for extra thrust and torque sensors. Furthermore, we provide a strong model capable of reliably forecasting Motor Electrical Speed (RPM), Thrust and Torque from unseen data, Motor Electrical speed predictions had a prediction accuracy of > 97% speed with an error < 2.5% of the data set range for 80% of the dataset and Thrust predictions had a prediction accuracy > 87% thrust with an error < 6% of the data set range for 80% of the dataset while Torque predictions had a prediction accuracy > 99% torque with an error < 1.2% of the data set range for 80% of the dataset . Each dataset is rigorously reviewed to reveal significant information and insights of motor properties. The dataset used in this work was obtained from RCtestBench 1580, which provided valuable information on motor characteristics, electrical signals, and mechanical outputs.

2. Introduction

Propeller thrust and torque are the principal forces and moments that are applied to the motor shaft at hover or low speeds, and which can be easily measured on a test bench that is stationary. It is easy to turn on and off the motor's three stages in order to check its rotational speed and challenging to compute the three forces and moments acting on the motor shaft during forward flight, though, without the aid of extra sensors. Study [1] modeled these forces and moments. [2] Designing and implementing A quadcopter's attitude control algorithm must be developed through a protracted process that involves simulation and in-flight testing. Due to potential design flaws like unmodeled dynamics, most control systems necessitate an experimental phase on the physical system for validation. This is because unexpected performance can arise. [3] and [4] Because of this, test platforms that evaluate controller performance in a setting that is risk-free for both the user and the vehicle are required to enable the shift between numerical and experimental analysis. [5] Bart and Joris presented how to use the recorded rotational speed, throttle setting, and input voltage to sense the propeller torque and current of a multirotor without the need for extra torque sensors. Their model achieved <0.01 Nm error or 4.6% of the data set range for 90% of the data set and <0.5A error for 90% of cases [6] The value of thrust stand data is demonstrated in this study, which uses an RC Benchmark thrust stand to investigate the influence of a leading-edge comb adjustment on propeller noise and thrust [7] The study explores towards using machine learning, primarily neural networks, to control drones rather than standard pre-programmed models. It uses methods such as non-linear regression and neural networks to learn the drone's behavior and anticipate its future motions [8] This research investigates three machine learning-based obstacle detection models for drones: a classical BP neural network, a classical GA-BP network, and an upgraded GA-BP network. All models were evaluated on a dataset of 150 training samples. Results include convergence curves [9] On a thrust stand, experiments are conducted to

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3. Methodology

System Overview and Test Setup

RCTestBench 1580 is a cutting-edge platform for testing the performance and dependability of remote controlled devices. This tool aims to drastically reduce the time required for characterising, testing, and building brushless motor propul- sion systems. Table I, Fig. 1 and Fig. 2 show the test setup overview. Once attaching all the mounted parts. Prior to the propulsion system being fitted, the digital thrust stand was calibrated using an internal calibration scheme and a calibration weight. Next, the battery, ESC, motor, and propeller were mounted on the digital thrust stand. The test stand uses robust software for automated control and data logging, and it connects to your computer via USB. The Scripting Interface can be used to write custom programmes that can be used to manually operate the ESC. Additionally, safety cutoffs can be implemented to prevent damage to the components.

Overview of Components Used

Component	Details
Data Collection Software	RCbenchmark - GUI 1.2.1
Hardware	RCbenchmark Series 1580
Motor	A2212 10t 1400kv
Propeller	Robodo 1045R

Feature Selection: Identifying and selecting relevant fea- tures from the dataset that will be used as inputs to the machine learning model. The selection process considers the signifi- cance of each feature in predicting the motor performance. Features that have correlation and importance will be retained, while irrelevant or redundant features may be excluded to simplify the model.

Model Selection: In this step, an appropriate machine learning model is chosen to predict the motor characteristics. After thorough exploration, various machine learning algo- rithms were considered, with a focus on regression models. This choice was informed by the observation that most of the features exhibit linear relationships and possess continuous values. Additionally, the selection process involved evaluating each model's performance and suitability for accurately cap- turing the underlying patterns in the dataset

4. Model Implementation

i. Motor electrical speed model

Lasso Regression Model: Lasso regression, also known as Least Absolute Shrinkage and Selection Operator (LASSO), is a statistical technique used in machine learning to analyze regression. It addresses two main goals: Regularization which accomplishes this by using a regularization technique known as L1 regularization and Feature Selection which automatically identify and remove irrelevant features from the model. this penalty in lasso reduces the coefficients towards zero, and in rare situations, it can drive them to zero.

ii. Thrust model

Polynomial Regression Model: Polynomial regression is a regression analysis technique that models relationships that are not necessarily linear. It accomplishes this by fitting a poly- nomial function to the dataset.which uses a complex equation of degree for the predictions. Using a low degree polynomial may not represent the complexity of the connection, resulting in a poor fit and inaccurate predictions.Using a very high degree polynomial may result in the model fitting the training data excellently but failing to generalize effectively to new data (overfitting). Since voltage and current have a strong correlation, we solely utilise voltage as it is the primary factor influencing thrust and helps to eliminate multicollinearity.

5. Conclusion

In conclusion, This thorough testing and measurement pro- vided crucial insights into the nonlinear dynamics of bldc mo- tors, including metrics such as thrust, torque and Motor speed across a wide range of operational situations. By employing the regression models to analyze readily available input data, we have successfully eliminated the need for additional thrust and torque sensors. this model achieved Accurate and reliable predictions, unveiling hidden insights, Sensor less operation These findings strongly support the use of ML as an effective tool for drone motor modeling and to accurately forecast motor speed from throttle ESC input and thrust,torque from mo- tor speed,voltage and current input thereby improving motor control mechanisms for maximum stability, flight endurance, and energy efficiency. the integration of machine learning techniques not only enhances the accuracy and reliability of motor predictions but also heralds a new era of innovation and efficiency in drone technology

6. References

1. W. Khan and M. Nahon, "A propeller model for general forward flight conditions," International Journal of Intelligent Unmanned Systems, vol. 3, Nov. 2015.
2. Y. Yu and X. Ding, "A quadrotor test bench for six degree of freedom flight," Journal of Intelligent Robotic Systems, vol. 3, 2012/12/01 2012.
3. N. Vitzilaios and N. Tsourveloudis, "An experimental test bed for small unmanned helicopters," Journal of Intelligent and Robotic Systems, vol. 54, pp. 769–794, 05 2009
4. U. Veyna, S. Garcia-Nieto, R. Simarro, and J. V. Salcedo, "Quad- copters testing platform for educational environments," Sensors, vol. 21, no. 12, 2021. [Online]. Available: https:// www.mdpi.com/1424- 8220/21/12/4134
5. B. Theys and J. De Schutter, "Virtual motor torque sensing for multirotor propul- sion systems," IEEE Robotics and Automation Letters, vol. PP, pp. 1–1, 03 2021.
6. M. Callender, "Uas propeller/rotor sound pressure level reduction through leading edge modification," Journal of Applied Mechanical Engineering, vol. 06, 01 2017.
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Addendum

As I began converting the academic paper into HTML, I researched the appropriate HTML5 tags that would best reflect the structure of a formal document. My goal was to ensure that each section of the paper was marked up semantically, providing both clarity for the reader and accessibility for assistive technologies. Here’s an overview of my process and the choices I made for specific tags:

Planning the Structure and Choosing `article` Tags: After researching how to structure documents in HTML, I learned that `article` is a semantic tag used for self-contained content. Given that the paper and the addendum were distinct sections, I decided to use two `article` tags: one for the main paper and another for the addendum. This clearly separates the content and makes the document easier to navigate. Each article encapsulates its own logical unit, with the first containing the body of the academic paper and the second the explanation of the HTML structure.

Using `header` and `address` for the Title and Author Information: Initially, I thought about simply using paragraphs for the title and author names. However, after further research, I discovered that the `header` tag is specifically designed to group introductory content such as the title, and the `address` tag is used to provide contact information. Therefore, I wrapped the title and author details within a `header` block, and each author’s contact information within an `address` block to improve semantic clarity. I found that using `address` was more meaningful than just plain `p` tags because it clearly indicates to both users and browsers that this section contains the author’s contact information.

Structuring the Content with `section` Tags: I initially planned to use `div` tags to separate different parts of the paper, but through my research, I found that `section` tags are more appropriate for dividing a document into thematic areas. Each major part of the paper (e.g., Abstract, Introduction, Methodology) was thus enclosed in its own `section`, with headings (`h2`) marking the beginning of each section. This choice provided better semantic structure and allows screen readers and search engines to understand the organization of the document more effectively.

Creating Hierarchical Headings: I used an `h1` tag for the title of the paper and `h2` tags for major sections like “Introduction” and “Conclusion.” For subsections, such as “System Overview and Test Setup,” I used `h3` tags to maintain a clear structure. This made the document easier to navigate, as the headings clearly outlined the flow of the paper.

Tables for Data Representation: When I first tried to present the component details, I used `p` tags, which didn’t provide proper structure for tabular data. After researching how to represent tabular information, I switched to using a `table` tag with `thead` for the table header and `tbody` for the body content. This allowed me to structure the data meaningfully, and the use of CSS for borders improved readability. I also added a `caption` tag to describe the table, improving accessibility for screen readers.

Inserting Citations with Links: At first, I just wrote out citations like [1] in plain text, but I realized this wasn’t very interactive or informative. I researched how to link citations, and I learned to use the `a` tag to link each citation in the text to the corresponding reference at the bottom of the document. I assigned id attributes to each reference, allowing me to create internal links from the citations in the paper body to the reference list. This greatly improved navigation and made the document more interactive.

Styling Challenges: I initially struggled with styling the content inline, which made the HTML cluttered and hard to manage. After researching best practices, I created a `style` block in the `head` section to centralize the CSS. This made it easier to manage and edit styles, especially for the table and headings. I used border-collapse: collapse; to ensure the table cells shared borders and added some padding for better readability. This separation of style and content made the HTML cleaner and easier to update.

Last updated: 09/16/2024 15:07:30

3. HTML Source code

```html
<!DOCTYPE html>
<html lang="en">
  <head>
    <meta charset="UTF-8" />
    <meta name="viewport" content="width=device-width, initial-scale=1.0" />
    <title>Drone Motor Modeling Using Machine Learning</title>
    <style>
        body {
            width: 85%;
            margin-left: 5em;
        }
        th, td {
            border: 1px solid black;
        }
        h1, h2 {
            text-decoration: underline;
        }

    </style>
  </head>
  <body>
    <article>
        <header>
```

```html
            <h1>DRONE MOTOR MODELING USING MACHINE LEARNING </h1>
            <address>
                <p><strong>Authors:</strong></p>
                <p>Dheeraj Tangella</p>
                <p>Dept. of Electronics and Communication Engineering, Indian Institute of
Information Technology, Design and Manufacturing, Kancheepuram, Chennai 600127, India</p>
                <p>Email: <a href="mailto:edm20d003@iiitdm.ac.in">edm20d003@iiitdm.ac.in</a></p>

                <p>Dr. Selvajyothi K</p>
                <p>Dept. of Electronics and Communication Engineering, Indian Institute of
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            </address>
        </header>

        <section>
            <h2>1. Abstract</h2>
            <p><strong>Unmanned aerial vehicles (UAVs) rely significantly
                on their propulsion systems, with the motor and propeller being
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                into improving UAV performance and reliability by utilizing
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                motor performance by doing an in-depth analysis using regres-
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                estimate rotational speed and using rotational speed, voltage and
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                Furthermore, we provide a strong model capable of reliably
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                rigorously reviewed to reveal significant information and insights
                of motor properties. The dataset used in this work was obtained
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            <p>Propeller thrust and torque are the principal forces and
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```html
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                obstacle detection models for drones: a classical BP neural
                network, a classical GA-BP network, and an upgraded
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        can be used to write custom programmes that can be used to
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            <caption>Overview of Components Used</caption>
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                <tr>
                    <th>Component</th>
                    <th>Details</th>
                </tr>
            </thead>
            <tbody>
                <tr>
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                    <td>RCbenchmark - GUI 1.2.1</td>
                </tr>
                <tr>
                    <td>Hardware</td>
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                </tr>
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                regression analysis technique that models relationships that are
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        </p>
        <p>
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            Planning the Structure and Choosing `article` Tags: After researching how to structure
documents in HTML, I learned that `article` is a semantic tag used for self-contained content. Given
that the paper and the addendum were distinct sections, I decided to use two `article` tags: one for
the main paper and another for the addendum. This clearly separates the content and makes the
document easier to navigate. Each article encapsulates its own logical unit, with the first
containing the body of the academic paper and the second the explanation of the HTML structure.
        </p>
        <p>
            Using `header` and `address` for the Title and Author Information: Initially, I thought
about simply using paragraphs for the title and author names. However, after further research, I
discovered that the `header` tag is specifically designed to group introductory content such as the
title, and the `address` tag is used to provide contact information. Therefore, I wrapped the title
and author details within a `header` block, and each author’s contact information within an
`address` block to improve semantic clarity. I found that using `address` was more meaningful than
just plain `p` tags because it clearly indicates to both users and browsers that this section
contains the author’s contact information.
        </p>
        <p>
            Structuring the Content with `section` Tags: I initially planned to use `div` tags to
separate different parts of the paper, but through my research, I found that `section` tags are more
appropriate for dividing a document into thematic areas. Each major part of the paper (e.g.,
Abstract, Introduction, Methodology) was thus enclosed in its own `section`, with headings (`h2`)
marking the beginning of each section. This choice provided better semantic structure and allows
screen readers and search engines to understand the organization of the document more effectively.
        </p>
        <p>
            Creating Hierarchical Headings: I used an `h1` tag for the title of the paper and `h2`
tags for major sections like “Introduction” and “Conclusion.” For subsections, such as “System
Overview and Test Setup,” I used `h3` tags to maintain a clear structure.
            This made the document easier to navigate, as the headings clearly outlined the flow of
the paper.
        </p>
        <p>
            Tables for Data Representation: When I first tried to present the component details, I
used `p` tags, which didn’t provide proper structure for tabular data. After researching how to
represent tabular information, I switched to using a `table` tag with `thead` for the table header
and `tbody` for the body content. This allowed me to structure the data meaningfully, and the use of
CSS for borders improved readability. I also added a `caption` tag to describe the table, improving
accessibility for screen readers.
        </p>
        <p>
            Inserting Citations with Links: At first, I just wrote out citations like [1] in plain
text, but I realized this wasn’t very interactive or informative. I researched how to link
citations, and I learned to use the `a` tag to link each citation in the text to the corresponding
reference at the bottom of the document. I assigned id attributes to each reference, allowing me to
create internal links from the citations in the paper body to the reference list. This greatly
improved navigation and made the document more interactive.
        </p>
        <p>
            Styling Challenges: I initially struggled with styling the content inline, which made
the HTML cluttered and hard to manage. After researching best practices, I created a `style` block
in the `head` section to centralize the CSS. This made it easier to manage and edit styles,
```

```
especially for the table and headings. I used border-collapse: collapse; to ensure the table cells
shared borders and added some padding for better readability. This separation of style and content
made the HTML cleaner and easier to update.
        </p>
    </article>

    <footer>
        <p>Last updated:
            <span id="lastModified"></span>
        </p>
    </footer>
    <script type="text/javascript">
         var x = document.lastModified;
         document.getElementById('lastModified').textContent = x;
    </script>
  </body>
</html>
```