Optimization system that chooses the right trade-off between device performance and reliability concerns

A final project that is part of the requirement for the BSc degree

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Abstract

This project presents the development and implementation of "UltraAim Pro," an advanced system designed to optimize the balance between performance and reliability in computational devices. The advent of machine learning (ML) and neural networks (NN) has revolutionized the computational landscape, enabling machines to learn and make decisions autonomously. However, high-performance systems often face challenges in maintaining long-term reliability. "UltraAim Pro" addresses this critical issue by employing artificial intelligence (AI) to monitor and dynamically adjust the system's operational parameters.

The core of "UltraAim Pro" is a custom neural network developed on the Ultra96 platform, which adapts in real-time to ensure optimal performance without compromising the hardware's durability. The project included extensive Python programming, GUI development with Tkinter, and the integration of complex libraries for data visualization and neural network operations. Data preprocessing and the creation of an intuitive user interface were pivotal for the machine learning model's accuracy and user experience, respectively.

Throughout the project, numerous challenges were encountered and overcome, including software and UI defects, which were mitigated through structured planning and detailed architectural development. The acquired skills and knowledge spanned various technical and soft skills, including Python programming, system architecture, data preprocessing, and the development of robust system requirements (SRs).

The analysis of test results and system performance validated the effectiveness of "UltraAim Pro," highlighting its robustness under diverse conditions and its potential for predictive maintenance and performance optimization. Future enhancements to the system are planned to include comprehensive testing, efficiency improvements, feature expansion, and adaptability to emerging technologies.

This project not only enhances operational efficiency and hardware longevity but also establishes a new standard in the AI integration for performance and reliability optimization in computational devices.

Acknowledgements

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My journey would not have been the same without each of you. Thank you from the bottom of my heart.

Abbreviations and Symbols

Abbreviations	Meaning
AI	Artificial Intelligence
ML	Machine Learning
NN	Neural Network
GUI	Graphical User Interface
CPU	Central Processing Unit
GPU	Graphics Processing Unit
TTF	Time to Failure
MSE	Mean Square Error
R^2	Coefficient of Determination
ReLU	Rectified Linear Unit
MTTF	Mean Time To Failure
SR	Software Requirements
FPGA	Field-Programmable Gate Array
UART	Universal Asynchronous Receiver/Transmitter
ARM	Advanced RISC Machines (Processor Architecture)

Symbols	Description
λ	Failure rate
μ	Mean
σ	Standard deviation
$\sum$	Summation operator
$Z1j$	Output before activation in the first neural layer
$Z2j$	Output before activation in the second neural layer
$Z3$	Output before activation in the output neural layer
$A1j$	Activated output in the first neural layer
$A2j$	Activated output in the second neural layer
y	Activated output in the output layer (prediction)
w	Weights in the neural network
b	Biases in the neural network
xi	Input features to the neural network
yi	Actual output targets
$\hat{y}i$	Predicted output targets
$f()$	Activation function or output layer function

Table of Contents

1. Introduction

1.1. Engineering: A Historical Perspective

From Tools to Technology

The journey of engineering is one of turning the wheels of innovation, bridging the gap between conceptual blueprints and real-world technology. It began with simple tools of antiquity and evolved into the complex machinery that heralded the Industrial Age. Today, we stand at the cusp of the digital frontier, where advancements like computers and the Internet are not just tools but foundations of modern existence.

Figure1 - Image that representing the journey of engineering, generated via AI tool.
It visually illustrates the evolution of engineering from its early stages with simple tools to the modern
digital era, including the Industrial Age and the rise of computers and the Internet.

1.2. The Advent of Computational Intelligence

Machine Learning and Neural Networks: the new frontier

In the present era, Machine Learning (ML) and Neural Networks (NN) represent the top of computational intelligence. These aren't merely incremental upgrades to existing technology; they're paradigm-shifting approaches that enable machines to learn from experience and make decisions with minimal human intervention. ML and NN have become the architects of a new digital reality, powering innovations from intelligent virtual assistants to autonomous vehicles.
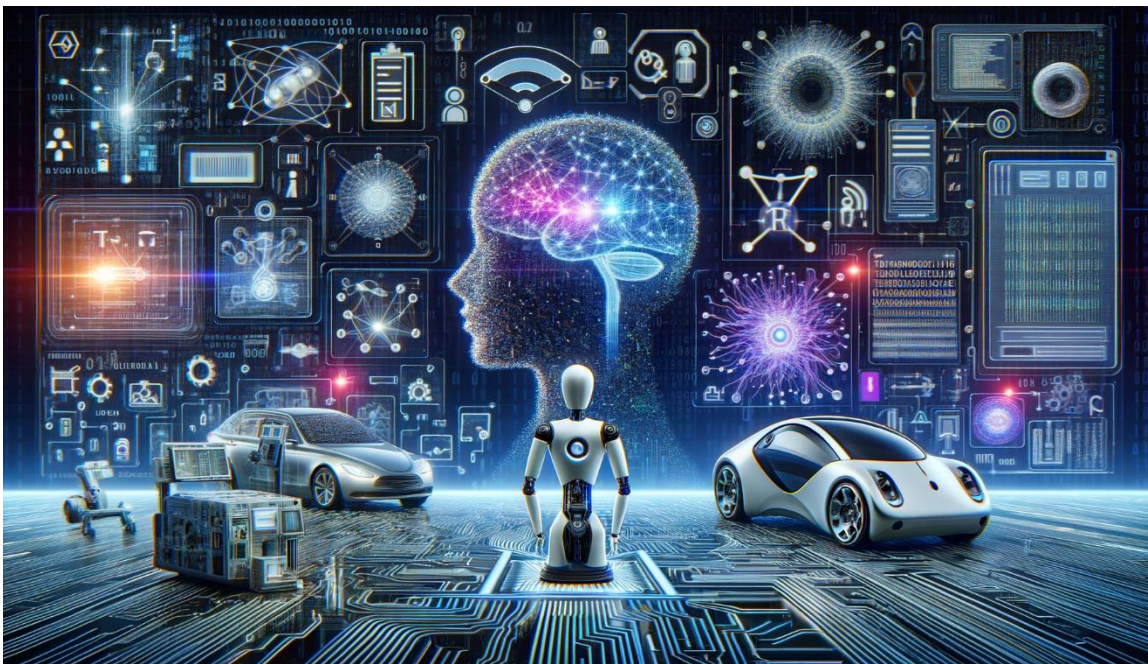
Figure2 - Image that illustrating the current era of Machine Learning and Neural Networks, generated via AI tool. It visually captures the advanced state of computational intelligence.
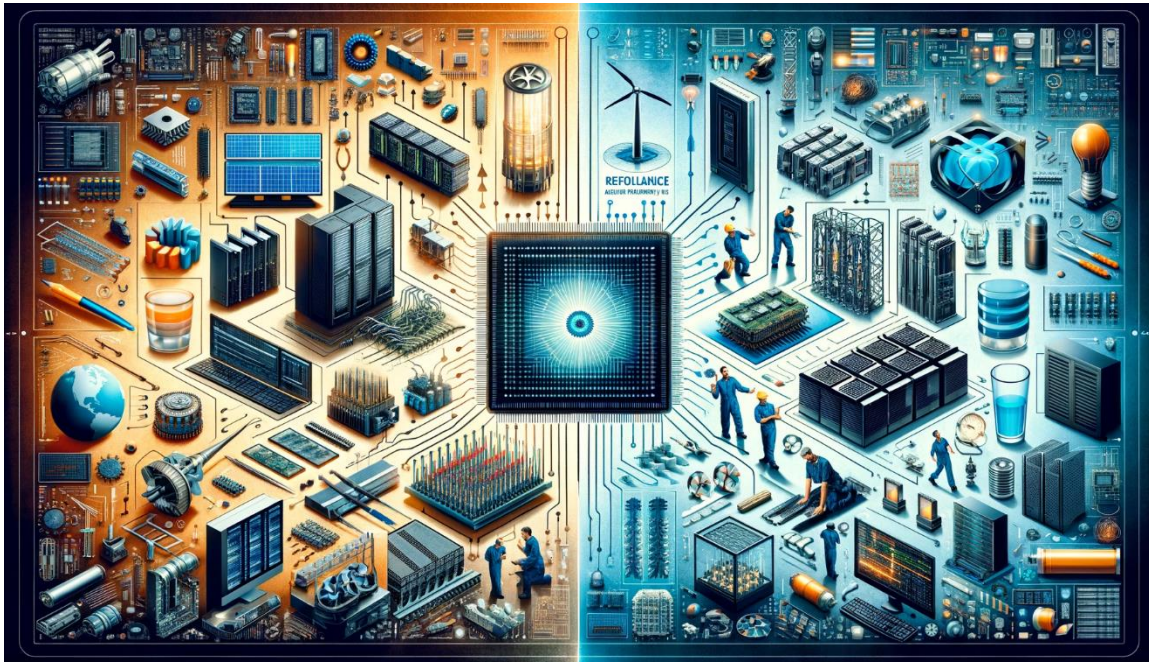
1.3. Balancing Act: Performance vs. Reliability

Ensuring Endurance in High-Performance Systems

"With great power comes great responsibility." This saying is particularly relevant in the context of engineering high-performance, reliable systems. The brilliance of ML and NN is shadowed by the challenge of sustaining their operational integrity over time. The engineering community strives not just to enhance the computational capabilities of devices but also to ensure their durability and dependability in the long run.

1.4. The Gap Sentence

Despite significant advancements in computational technology, particularly in neural networks and FPGA-based systems, a critical challenge remains- developing a reliable method to harmonize the high-level performance of these devices with their long-term reliability, ensuring their effectiveness across various applications, including high-demand environments.

Figure3 - Image generated via AI tool that illustrates the difficulties in balancing performance and long-term reliability in computational technology. It illustrates the contrast between high-performance computing technology and the challenges associated with ensuring reliability.

1.5. The Solution: UltraAim Pro

Addressing the challenge of balancing high performance with long-term reliability in computing devices, this project introduces "UltraAim Pro." This system, an abbreviation for Ultra96-based AI-Managed Performance and Reliability Optimization, is designed to navigate the trade-off between robust performance and consistent reliability.

"UltraAim Pro" leverages the advanced capabilities of the Ultra96 platform, employing AI to monitor and adjust the system's performance dynamics. At its core is a custom neural network that dynamically adapts to ensure the device operates within its optimal parameters, maintaining performance without compromising long-term reliability.

By integrating machine learning algorithms with a comprehensive understanding of hardware constraints and performance metrics, 'UltraAim Pro' aims to enhance operational efficiency and extend the lifespan of the hardware it manages. This approach represents a significant advancement in the fields of predictive maintenance and performance optimization, establishing a new standard at the intersection of AI and hardware longevity.

2. Purpose

2.1. Design Condition

‹ Application Structure and Workflow: Ensuring a robust and user-friendly application that smoothly handles data flow from input to output.

‹ Data Processing: Implementing effective methods for cleaning, normalizing, and managing data throughout the application.

‹ Neural Network Model: Designing an efficient neural network architecture, focusing on the right balance of layers and functions, and ensuring effective training and evaluation strategies.

‹ User Interface and Visualization: Creating an intuitive interface for user interactions and developing clear visualization tools for model results and data analysis.

‹ Performance and Reliability: Balancing the system's computational efficiency with accuracy, ensuring the model's robustness and reliability under different conditions.

‹ Testing and Validation: Conducting thorough testing of the system's components and validating the model with real-world data to ensure practical applicability.

2.2. System Requirements

‹ GUI Requirements:

Intuitive Design: A user-friendly interface that is easy to navigate, allowing users to input data, configure settings, and view results effectively.

Visualization Tools: Robust features for visualizing data, model training progress, and results, including graphs and charts.

Interactive Elements: Responsive elements like buttons, sliders, and menus for user interaction and customization.

‹ Data Preparation:

Data Ingestion: Capability to load and process data from various sources, ensuring flexibility in data formats.

Data Cleaning: Features for handling missing data, outliers, and anomalies to prepare the dataset for accurate model training.

Preprocessing Functionality: Tools for data normalization, feature extraction, and transformation to make the data suitable for neural network training.

‹ Coverage of Corner Cases:

Error Handling: Robust error handling mechanisms to deal with unexpected inputs or system behaviors.

Scalability for Diverse Data: Ability to handle diverse and evolving datasets, ensuring the system remains effective under various scenarios.

Flexibility in Model Training: Accommodating different training scenarios, including variations in data size, model complexity, and user-defined parameters.

3. System Overview

3.1.Overview of the Proposed System

"UltraAim Pro" system is a system designed to enhance the efficiency of FPGAs during stress conditions. It's part of a project that tackles the need for high performance while also aiming for the devices' long-term reliability. Utilizing the Ultra96 board's capabilities, "UltraAim Pro" employs AI and a custom neural network to adjust the FPGA's operations. This smart system continuously learns and adapts, ensuring that the device functions at its best without risking future performance. The software gathers data crucial for training the neural network, which then makes accurate predictions to optimize the FPGA's efficiency. Through this, "UltraAim Pro" not only boosts current operations but also contributes to the hardware's longevity, balancing immediate results with sustainable use.

3.2.Hardware Design Considerations

For the "UltraAim Pro" system, choosing the right hardware is critical to maintain reliable performance under stress. The Ultra96 development board, with its Xilinx Zynq UltraScale+ MPSoC, serves as the central component due to its dependable operation in a wide temperature range, from -40°C to +85°C, and its ability to operate within a broad voltage range, ensuring stable power delivery even under varying conditions. At the heart of this board is the Xilinx Zynq UltraScale+ MPSoC, a multi-processing powerhouse designed to handle a wide range of tasks. It combines ARM Cortex-A53 and ARM Cortex-R5 cores, providing both the processing power needed for running software-based applications and real-time processing capabilities essential for monitoring and adjusting system performance. Additionally, the MPSoC includes an ARM Mali GPU, which excels in parallel processing tasks, making it well-suited for AI and machine learning workloads.

One of the standout features of this MPSoC is its programmable FPGA fabric. This programmability allows you to tailor the hardware to your project's specific requirements, making it adaptable to the demands of performance optimization tasks. Whether you need to implement custom hardware accelerators or modify the FPGA configuration for different stress scenarios, the Ultra96 board offers the versatility needed to excel in diverse computing challenges.

In summary, the Ultra96-V2's combination of FPGA programmability, powerful ARM cores, real-time processing capabilities, and GPU support makes it an excellent choice for implementing AI, ML, and NN solutions. This versatility and adaptability are crucial for achieving optimal performance and efficiency in your "UltraAim Pro" project, particularly when dealing with dynamic optimization tasks. Together, these features make the Ultra96 development board the ideal foundation for your project, ensuring that it can reliably handle the demands of stress testing, performance optimization, and AI-based tasks.
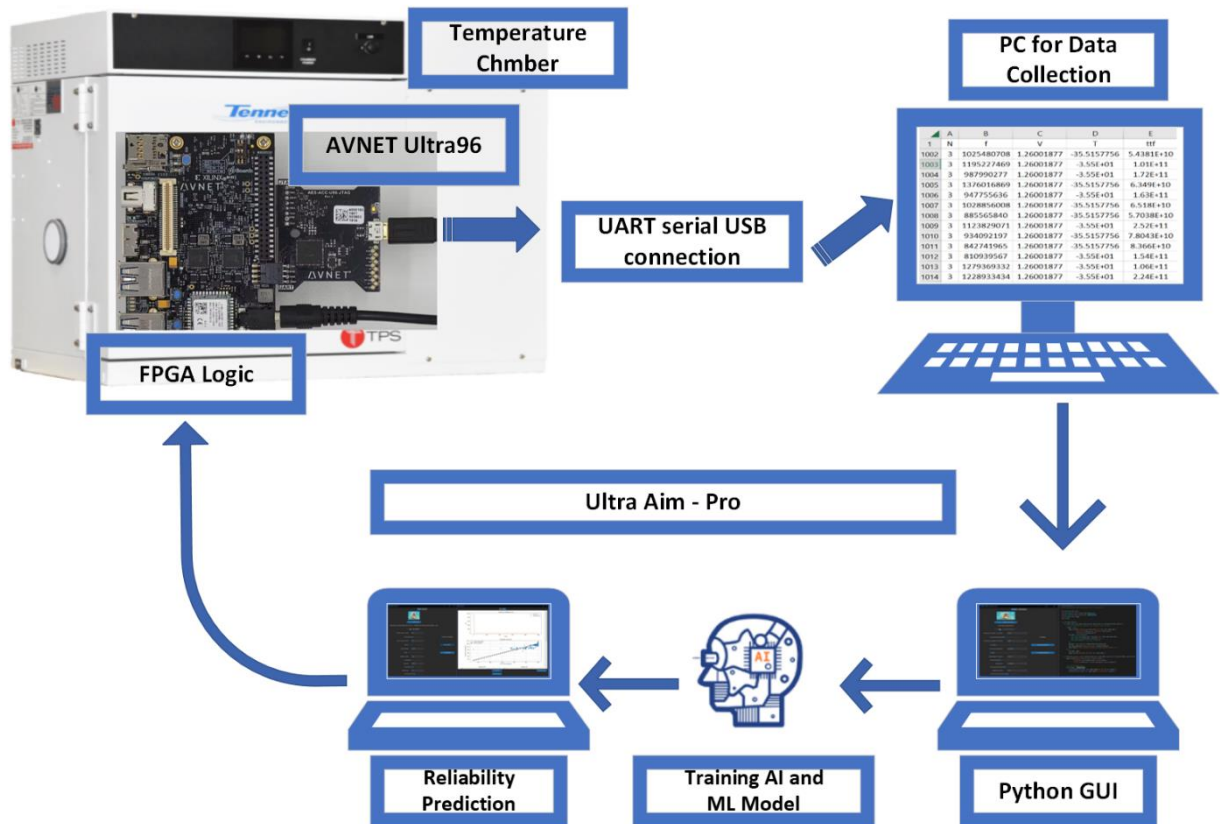
Figure4 : System Integration Diagram for the UltraAim Pro Project, showing the interconnection between the AVNET Ultra96 board inside a temperature chamber, FPGA logic configuration, and the UART serial USB connection to the PC for data collection. The diagram o

3.3.Software Design Considerations:

The software design of the "UltraAim Pro" system is strategically structured to enhance the performance and reliability of FPGAs under stress conditions.

The approach is grounded in a few key principles -

Modular and Scalable Architecture:

The software is designed with modularity in mind, ensuring each component, from data preprocessing to neural network modeling, operates as an independent module. This design facilitates scalability, allowing for easy updates and enhancements to individual components without disrupting the system's overall functionality.

Integration of AI and Machine Learning:

At the core of "UltraAim Pro" is a custom-built neural network, tailored to make intelligent decisions based on real-time data. The software is engineered to efficiently process and learn from this data, enabling it to predict and adjust the FPGA's operations for optimal performance.

Robust Data Handling and Preprocessing:

Given the importance of accurate data in training our AI model, the software includes a comprehensive data management framework. This includes advanced preprocessing techniques to ensure the quality and consistency of the data fed into the neural network.

User-Centric Interface and Visualization:

The software includes a user-friendly graphical interface, allowing for easy monitoring and interaction with the system. Visualization tools are integrated to provide clear insights into the FPGA's performance and the system's decision-making processes.

Emphasis on Real-Time Performance and Reliability:

The design prioritizes real-time data processing and decision-making, ensuring minimal latency in system responses. Furthermore, the software is built to be robust and reliable, capable of maintaining performance under various operational stress scenarios.

Continuous Learning and Adaptation:

A key feature of the software is its ability to continuously learn from new data and adapt its strategies for FPGA optimization. This ensures that "UltraAim Pro" remains effective over time, adjusting to new challenges and operational conditions.

Efficient Resource Utilization:

Considering the limited resources available on embedded systems like FPGAs, the software is optimized for efficiency. This includes careful management of computational resources and memory, ensuring that the system delivers high performance without overburdening the hardware.

By adhering to these principles, the "UltraAim Pro" software is uniquely positioned to enhance the efficiency of FPGAs during stress conditions, balancing immediate performance improvements with long-term device reliability

Figure5 - Conceptual Mind Map of the UltraAim Pro System: Illustrating the Modular Architecture, AI & ML Integration, Data Management, User Interface & Visualization, Performance & Reliability, Adaptive Learning, and Resource Optimization Components with their Interrelated Features and Functions.

4. System Development

4.1.Software Development Process

The development process for the "UltraAim Pro" system was carefully structured to ensure robustness, scalability, and maintainability. The approach adopted is an iterative and incremental development model, allowing for continuous integration and testing of new features and components.

Requirement Analysis:

The System Requirements for the "UltraAim Pro" were designed with three main goals in mind:

1. Learning and Skill Development: The integration of academic knowledge with the acquisition of new, practical skills not typically included in the curriculum. This approach aimed to provide a more comprehensive educational experience.

2. Proficiency with Engineering Tools and Methods: The project was undertaken to ensure familiarity with contemporary engineering tools and methods, preparing for immediate effectiveness in professional practice post-graduation.

3. Creation of a Practical and User-Oriented System: The design focused on developing a system that addresses real-world problems while maintaining ease of use. The system architecture was also structured to allow for modifications for future project applications.

Table 1- High level Software Requirements for "UltraAim Pro" application.

ID	Description	Rational
SR-4.1.1	**User Authentication:** The system shall provide a secure login interface requiring username and password to authenticate users.	To ensure data privacy and system security by restricting access to authorized users.
SR-4.1.2	**Data Upload and Validation:** The system shall allow users to upload datasets and validate them for integrity and format correctness.	To maintain data quality and ensure compatibility with the system's processing capabilities.
SR-4.1.3	**Configurable Neural Network:** The system shall enable users to configure neural network parameters such as layer units and learning rate.	To provide flexibility and allow users to tailor the neural network to specific data sets and use cases.
SR-4.1.4	**Feature Engineering and Preprocessing:** The system shall provide functionality for data preprocessing and feature engineering to prepare data for model training.	To enhance model accuracy and performance by ensuring data is in the optimal format for processing.
SR-4.1.5	**Training and Validation:** The system shall facilitate the training of the model with user-provided data and perform validation using a specified validation split.	To build a robust model that generalizes well to new data and to prevent overfitting.
SR-4.1.6	**Performance Monitoring:** The system shall display real-time training progress, including loss and accuracy metrics.	To provide immediate feedback to the user, enabling monitoring and adjustments as needed during training.
SR-4.1.7	**Result Analysis and Visualization:** The system shall offer analysis tools and visualization of training results such as loss and accuracy plots post-training.	To allow users to understand model performance visually and make data-driven decisions.
SR-4.1.8	**Report Generation:** The system shall be capable of generating comprehensive reports documenting the model's performance and configurations.	To facilitate the evaluation of the model and to provide documentation for future reference.
SR-4.1.9	**Export Functionality:** The system shall allow users to download the trained model, plots, and analysis reports.	To enable portability and further analysis of the results outside the system environment.
SR-4.1.10	**Scalability and Maintenance:** The system shall be designed to accommodate future expansions and updates without significant redesign.	To ensure the longevity and adaptability of the system to new requirements and technologies over time.

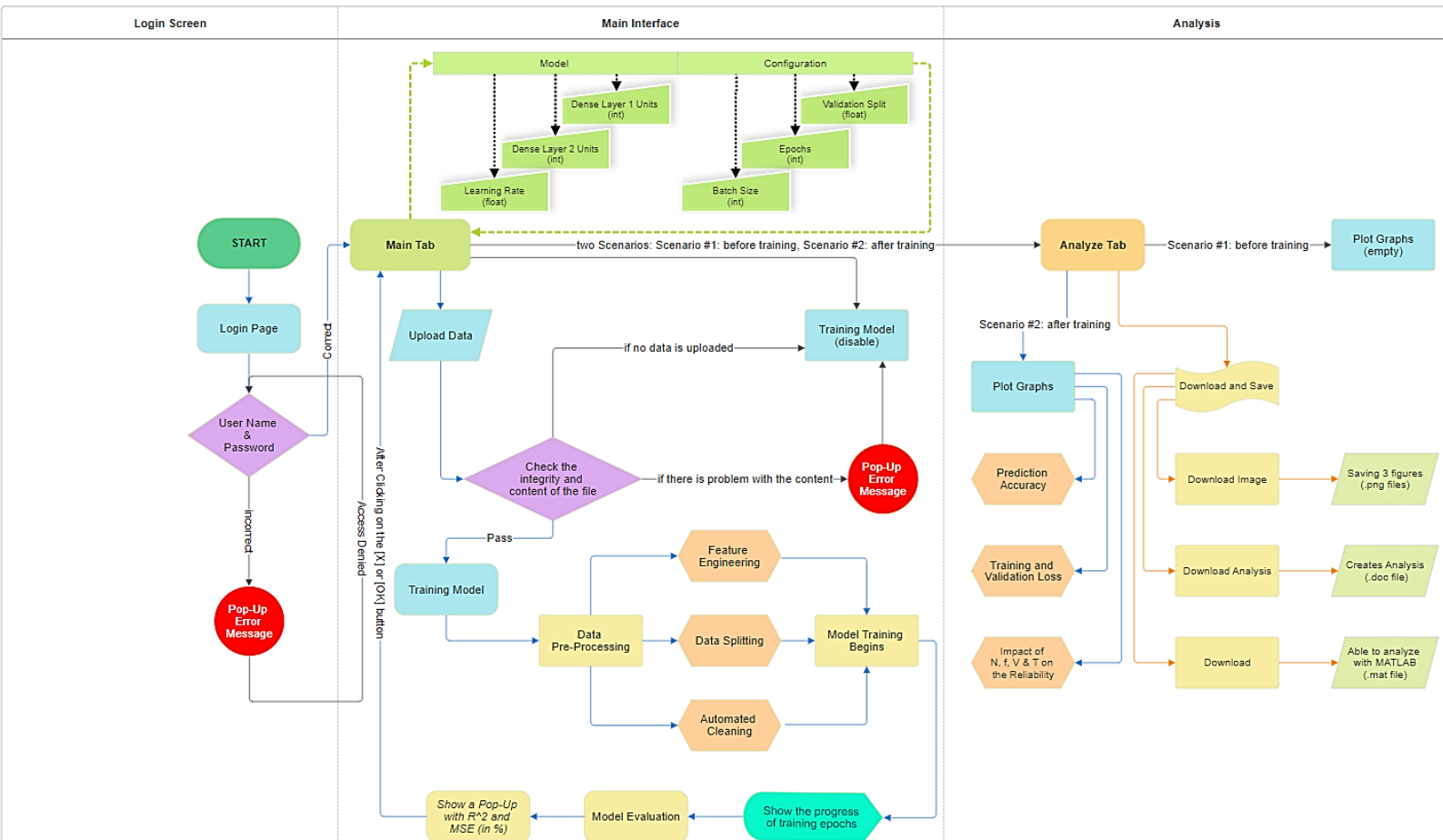UltraAim Pro – System Flow:

Figure6 - UltraAim Pro system flow chart outlining the structure and workflow. It also shows different scenarios and paths depending on the state of the application.

Project Workflow Description:

1. Initialization: Login Screen

The process begins with the Start, leading the user to the Login Page.

The user is required to enter a Username & Password.

If the credentials are incorrect, a Pop-Up Error Message is displayed, prompting the user to try logging in again.

2. Main Interface: Configuration and Data Management

Once logged in, the user interacts with the Main Tab, where they can Upload Data for analysis.

The uploaded data undergoes integrity checks to ensure proper format and content. If any issues are detected, a Pop-Up Error Message is shown.

Upon successful validation, the user can proceed to the Training Model stage. If no data is uploaded, the model training option remains disabled.

3. Model Setup and Initialization

The user configures the neural network model by setting parameters such as Dense Layer 1 Units, Dense Layer 2 Units, Learning Rate, Validation Split, Epochs, and Batch Size.

These configurations are crucial as they define the architecture and training regimen of the neural network.

4. Data Preparation and Model Training

The data is prepared through Feature Engineering, Data Pre-Processing, and Data Splitting which includes partitioning the data into training and validation sets.

Automated Cleaning is applied to ensure data quality.

Model training begins with the specified parameters, during which the progress of training epochs is shown to the user.

Upon completion, the Model Evaluation takes place, providing metrics such as R^2 and MSE in a pop-up window.

5. Analysis and Reporting

The Analyze Tab presenting different scenarios before and after training.

Initially, the Plot Graphs are empty. After training, they display Training and Validation Loss, as well as Prediction Accuracy.

The user can download various outputs like graphs, analysis, and even raw data for further processing in .png, .doc, and .mat file formats, respectively.

6. Post-Training Analysis

The system offers an in-depth analysis feature where users can download the analysis report and Plot Graphs illustrating the model's performance.

There's an option to analyze the impact of different features like Number of Dynamic Logic, Frequency, Voltage, Temperature and Training on the Reliability of the model.

For advanced analysis, users have the option to work with MATLAB by downloading .mat files.

7. Final Output

The final stage allows the user to Create Analysis reports in .doc format, providing a comprehensive overview of the model's performance and any insights derived from the training process.

4.2.Algorithm Design and Implementation

Data Preprocessing and Feature Engineering:
Data preprocessing and feature engineering constitute foundational steps in the preparation of datasets for efficient model training. Initially, raw data is subjected to a thorough cleansing process, which involves the identification and correction of errors, handling of missing values, and removal of irrelevant information. Subsequently, feature engineering is undertaken to transform raw data inputs into formats that are more suitable for machine learning algorithms.

During feature engineering, domain knowledge is applied to create features that can potentially improve the model's performance. This stage might include generating new data fields from existing ones, encoding categorical variables, or discretizing continuous variables for better representation.

Standard scaling is applied as part of the preprocessing to normalize feature values, ensuring consistent scale across all inputs. This is achieved by subtracting the mean and dividing by the standard deviation for each feature, as illustrated by the formula: $z = \frac{x-\mu}{\sigma}$

Where:
- x is the original feature value.
- μ is the mean of the feature values.
- σ is the standard deviation of the feature values.

The importance of standard scaling lies in its capacity to enhance the performance of machine learning models, especially those sensitive to the magnitude of inputs, such as neural networks. It ensures that each feature contributes equally to the computation of distances and gradients during the training phase.

Following the application of standard scaling, reliability calculations incorporated into the dataset as a predictive feature, reliability is a key metric, essential for forecasting the lifespan of electronic components. It is quantified through a well-established method in reliability engineering, employing an exponential decay function to model the probability of failure over time.

The reliability percentage is thus calculated as: $R(\%) = e^{-\lambda t} \times 100$
Where:
- λ is the failure rate, calculated as $\lambda = \frac{1}{MTTF}$
- t is the time period for which the reliability is being assessed.
- MTTF is the time to failure.

This formula is premised on the understanding that failures typically occur in an exponential manner with respect to time. The reliability percentage thus denotes the likelihood that a component will maintain its required functionality without failure throughout the duration 't'. It is this predictive reliability metric that is then applied as a feature within the model, allowing the algorithm to consider the time-dependent operational stability of the components under analysis.
The integration of such a reliability feature underscores the system's capacity to anticipate component performance degradation, thereby contributing to more informed and proactive maintenance decision-making.

Neural Network Architecture and Activation Functions:
The neural network architecture within this project is constructed as a multi-layered, feedforward network, employing densely connected layers. This configuration is key to defining the model's ability to identify complex patterns and make predictions from the data.

- **Inputs:** The network accepts a set of input features, denoted generally as [a1, a2, ..., an], which correspond to the various attributes of the dataset being processed.

- **Layer 1 (Dense, ReLU):** The first hidden layer is a dense layer with a predefined number of neurons, each utilizing a weight matrix W1 and a bias vector b1. The layer's output, Z1, is calculated as the weighted sum of the inputs plus the bias, and ReLU (Rectified Linear Unit) is applied as the activation function, providing the output A1 for each neuron:
$$A1_j = \max(0, Z1_j)$$
Where $Z1_j = \Sigma_i(a_i \times \omega_{ij}) + b1_j$

- **Layer 2 (Dense, ReLU):** The second hidden layer, similar in structure to the first, uses its own set of weights W2 and biases b2. It takes the output from the first layer, A1, as its input, and applies the ReLU activation function to yield its output, A2:
$$A2_j = \max(0, Z2_j)$$
Where $Z2_j = \Sigma_i(A1_i \times \omega_{ij}) + b2_j$

- **Output Layer (Dense):** The final output layer consolidates the information from the previous layer and produces a single output, y, which represents the reliability score. The computation for this layer's output is:
$$y = f(z3)$$
Where $Z3 = \Sigma_i(A2_i \times \omega_i) + b3$, and $f(z3)$ is an activation function appropriate for the output type, which is typically a linear function for regression tasks.
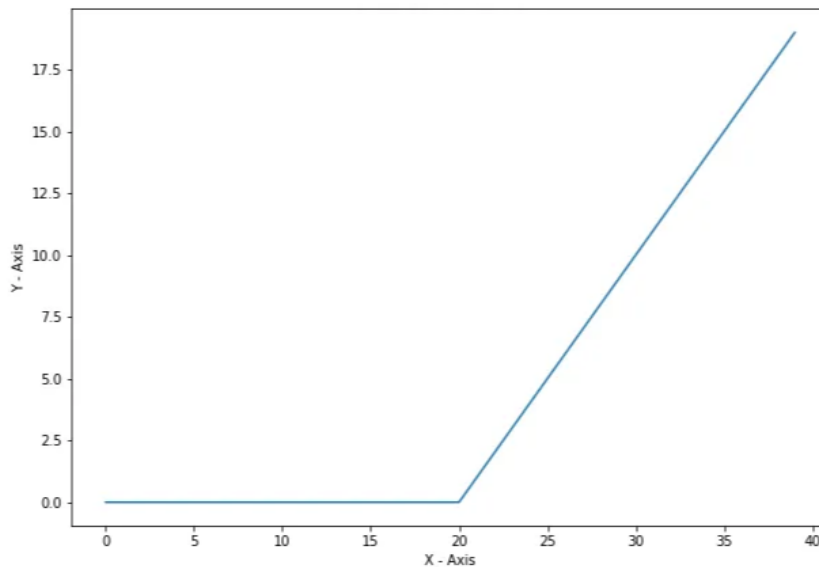
Figure7 - ReLU activation function graph where X-Axis is the input of the neuron

~ 21 ~

This architectural design, with ReLU activation functions in the hidden layers, is instrumental for capturing non-linear relationships without falling into the pitfalls of gradient vanishing issues that can occur with other activation functions like sigmoid or hyperbolic tangent. The layers' compositions, namely the number of neurons and the activation functions, have been carefully calibrated to optimize the network's performance for the specific task of reliability assessment in microelectronic components.

$$Z1_j = \sum_i (x_i \cdot w_{ij}^{[1]}) + b_j^{[1]}$$

$$A1_j = \max(0, Z1_j)$$

$$Z2_j = \sum_i (a_i^{[1]} \cdot w_{ij}^{[2]}) + b_j^{[2]}$$

$$A2_j = \max(0, Z2_j)$$

$$Z3 = \sum_i (a_i^{[2]} \cdot w_i^{[3]}) + b^{[3]}$$

$$y = f(Z3)$$
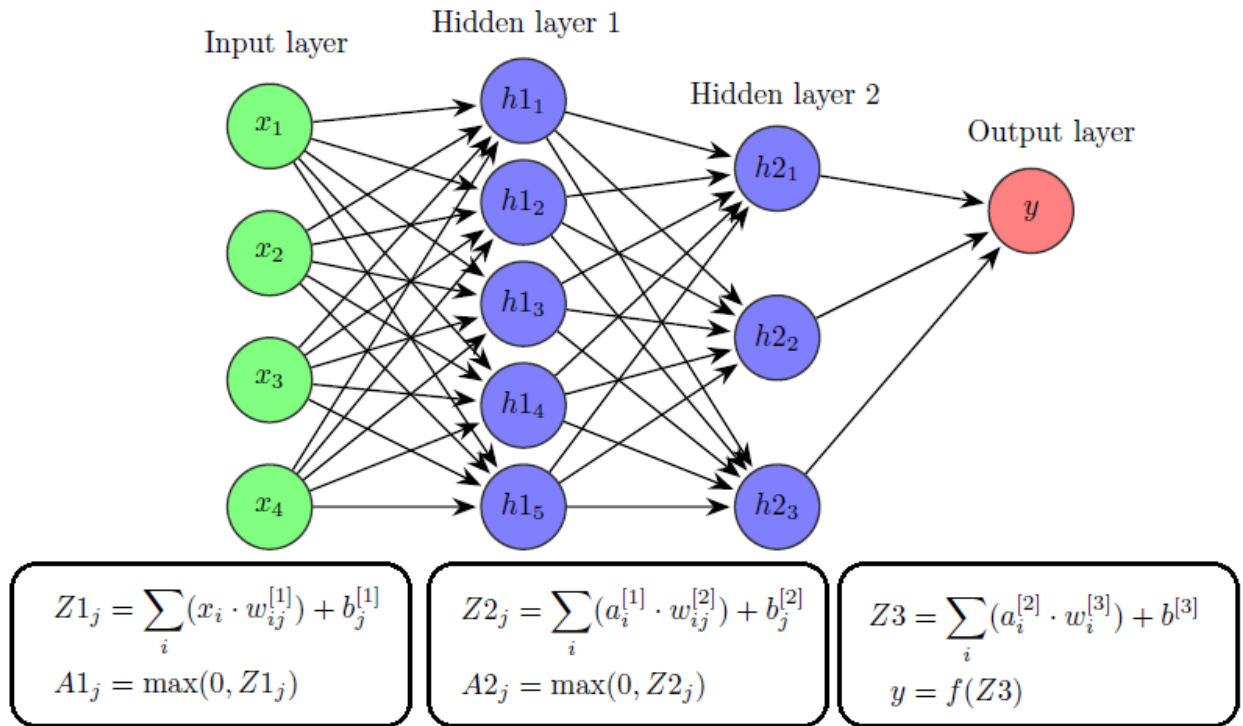
Figure8 - This diagram visualizes the structure of a multi-layer feedforward neural network. It consists of an input layer that receives features x_1, x_2, ..., x_n, two hidden layers with neurons $h1_j$, $h2_j$ applying the ReLU activation function, and an output layer producing the final prediction y. Mathematical expressions beneath each layer detail the computations within the network: weighted sums $Z1_j$, $Z2_j$, Z3 and activations $A1_j$, $A2_j$, y. The ReLU activation is defined as max(0,Z) for hidden layers, with the output layer's activation function f dependent on the specific task.

The entire network structure and training process are logged and monitored for performance evaluation and troubleshooting, ensuring a high level of transparency and control over the model training lifecycle.

Optimization Algorithm and Loss Function:
An optimization algorithm, like SGD or Adam, is employed to minimize the loss function, which measures the discrepancy between the model's predictions and the actual data. The loss function's role is crucial in steering the optimization algorithm towards improved model performance.

Model Training Strategy:
Model training is an iterative process that includes forward propagation, backpropagation, and epoch-wise adjustments. Early stopping is employed as a regulation strategy to prevent overfitting, ensuring the model retains its ability to generalize to new data.

Model Evaluation and Validation:
The model's effectiveness is assessed through evaluation metrics such as accuracy, precision, recall, and F1-score. Validation involves using a separate data set to test the model, ensuring its performance holds up against previously unseen data.

Data Handling Techniques:
Data splitting is used to divide the dataset into training, validation, and test sets, which is essential for an unbiased evaluation of the model. Parameter optimization heuristic techniques are applied to fine-tune the model's hyperparameters for optimal performance.

Post-Processing of Model Outputs:
After model training, an inverse transformation is applied to the scaled data to interpret the model's outputs in their original scale, facilitating a clear understanding of the results.

5. Testing and Evaluation

5.1.Performance Validation and System Assessment

Validation of a system's performance is critical step to confirm that it functions according to its design speciation's and meets the user requirements It involves rigorous testing to ensure reliability, efficiency, and accuracy of the system under various conditions.

Test Environment Setup:

- **Python development environment:**
  - 'pandas' for data manipulation and analysis.
  - 'scikit-learn' for machine learning tasks.
  - 'numpy' for numerical operations.
  - 'joblib' for saving and loading Python objects.
  - 'PIL' (Pillow) for image processing.
  - 'scipy' for scientific computing.
  - 'matplotlib' for data visualization.
  - 'tensorflow' and keras for building and training neural networks.

- **Visual Studio Code:** An IDE (Integrated Development Environment) used for writing, editing, and debugging the Python code.
- **CPU vs. GPU Computing:** The neural network/AI model runs on the CPU, which is adept at handling diverse tasks.
  > CPU Computing: suitable for a wide range of tasks, used in this project for its versatility.
  > GPU Computing: ideal for parallel processing tasks like deep learning, not used in this project due to the scale of the computations, however, it can offer faster processing for a larger dataset and complex models.

Testing Methodology:

- **Unit Testing:** For testing individual components of the software.
- **Integration Testing:** To ensure that different parts of the application work together.
- **Performance Testing:** Assessing the system's response and stability under various load conditions.

<u>Performance Metrics:</u>

- **Latency:** The response time of the system.

- **Error Rates:** Frequency of errors during operation.

- **Resource Utilization:** Monitoring CPU, memory, and storage usage.

5.2.System Efficiency and reliability Tests

Features and Tests Covering System Requirements:

The "Ultra Aim Pro" application was designed with a robust set of features that ensures

Effectiveness and utility:

- **SR-4.1.1: User Authentication**

    Feature: Secure login module.

    Test: Verify that login rejects unauthorized access and allows correct user credentials.

- **SR-4.1.2: Data Upload and Validation**

    Feature: Data management interface.

    Test: Confirm data integrity check and compatibility with system processing.

- **SR-4.1.3: Configurable Neural Network**

    Feature: Neural network configuration panel.

    Test: Adjust parameters and evaluate model performance changes.

- **SR-4.1.4: Feature Engineering and Preprocessing**

    Feature: Data preprocessing toolkit.

    Test: Implement feature selection methods and assess impact on model accuracy.

- **SR-4.1.5: Training and Validation**

    Feature: Model training engine.

    Test: Execute training sessions with validation splits and monitor for overfitting.

- **SR-4.1.6: Performance Monitoring**

    Feature: Real-time performance dashboard.

    Test: Monitor live metrics during model training to ensure progress is within expected

    ranges.

- **SR-4.1.7: Result Analysis and Visualization**

  Feature: Visualization and analysis module.

  Test: Generate and review loss and accuracy plots post-training.

- **SR-4.1.8: Report Generation**

  Feature: Automated report generator.

  Test: Create reports post-analysis and verify completeness and accuracy.

- **SR-4.1.9: Export Functionality**

  Feature: Export utility.

  Test: Export various outputs and validate the correctness outside the system environment.

- **SR-4.1.10: Scalability and Maintenance**

  Feature: Modular design for easy updates.

  Test: Simulate system scaling to evaluate performance under increased loads.

Future Improvements:

Building on SR-4.1.10, future enhancements could include:

- **Comprehensive Testing**: Develop a more extensive suit of tests, including stress, performance, and load testing, to ensure the application's robustness under various conditions.

- **Efficiency Improvements:** Optimize algorithms and resource management to reduce the computational load and improve the speed of model training and data processing.

- **Feature Expansion:** Introduce new features such as advanced analytics capabilities, support for additional data formats, and integration with other machine learning frameworks.

- **Adaptability to New technologies:** ensure that the system can be adapt to emerging technologies, such as new Neural Network architectures or hardware accelerators like GPUs for faster processing.

6. Analysis and Findings

6.1. Analysis of Test Results and System Performance

This section examines the performance metrics obtained from the tests conducted and interprets the system's operational effectiveness and robustness, correlating it with the outlined system requirements (SRs).

System Security Performance (SR-4.1.1):

Description of authentication mechanisms and encryption protocols tested.

Inform the user with an error alert and record all unauthorized access attempts.
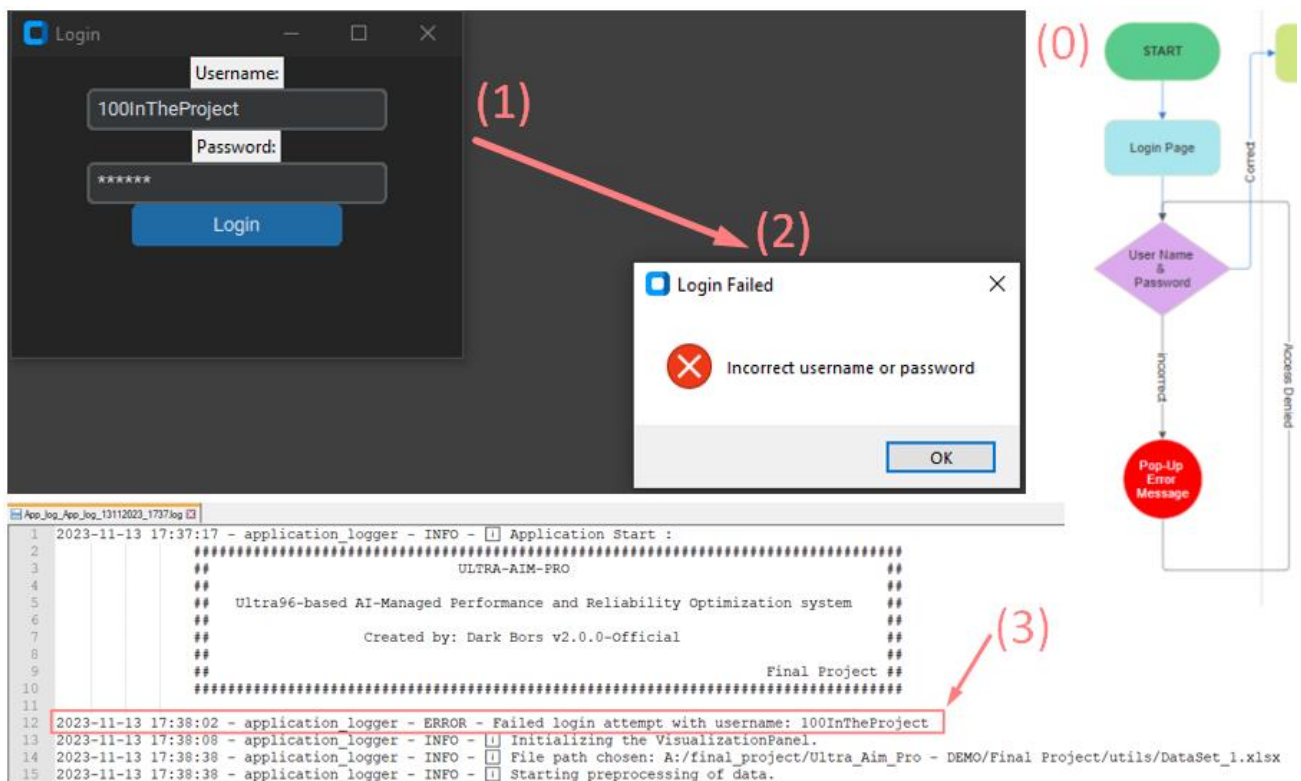
Figure9 - (0)Flow chart representing the behavior of the login process. (1) Login screen- wrong password was entered resulted in (2) error pop-up message indicating that an incorrect username or password was entered. (3) ERROR message was written in the log.

Data Handling Capabilities (SR-4.1.2 and SR-4.1.4):

Data Upload and Integrity Checks:

The process begins with the data upload protocol, which allows users to input their datasets into "Ultra Aim Pro". The system is designed to handle only .xlsx data formats with the primary requirement being that the data must be structured for the neural network to interpret. As part of the integrity check, the system scans the uploaded file for issues such as missing values, incorrect formats, and corrupt data.
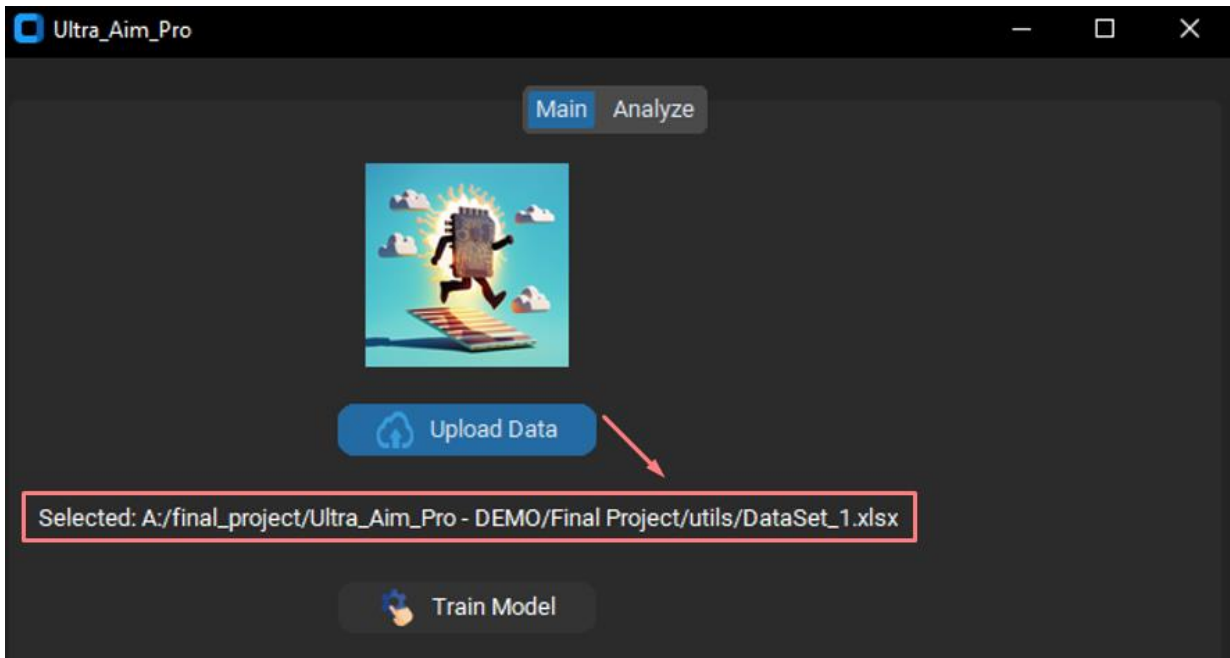
Figure 11 : The Ultra Aim Pro main interface displaying the data upload functionality. The screenshot highlights the user's ability to select a dataset for analysis, with 'DataSet_1.xlsx' currently loaded and ready for pre-processing.

Figure10 :Screen capture from the Ultra Aim Pro application log detailing the sequence of operations from initialization to model compilation. Key events include data loading, preprocessing, feature engineering, neural network initialization, and model training p

In **Error! Reference source not found.**, we can see the system initializing the process and selecting the file path for the dataset (see Line 16). This step is critical as it establishes the connection between the user interface and the data to be processed.

Data Preprocessing and Validation:

Once the file is uploaded, the system proceeds to preprocess the data. This includes cleaning the dataset by removing or correcting any anomalies, such as NaN values (as seen in **Error! Reference s ource not found.** 10 on Line 17), and engineering features to improve the model's performance. The preprocessing also involves normalizing and scaling the data, ensuring that the neural network receives inputs within an appropriate range, which is crucial for the model's accuracy.
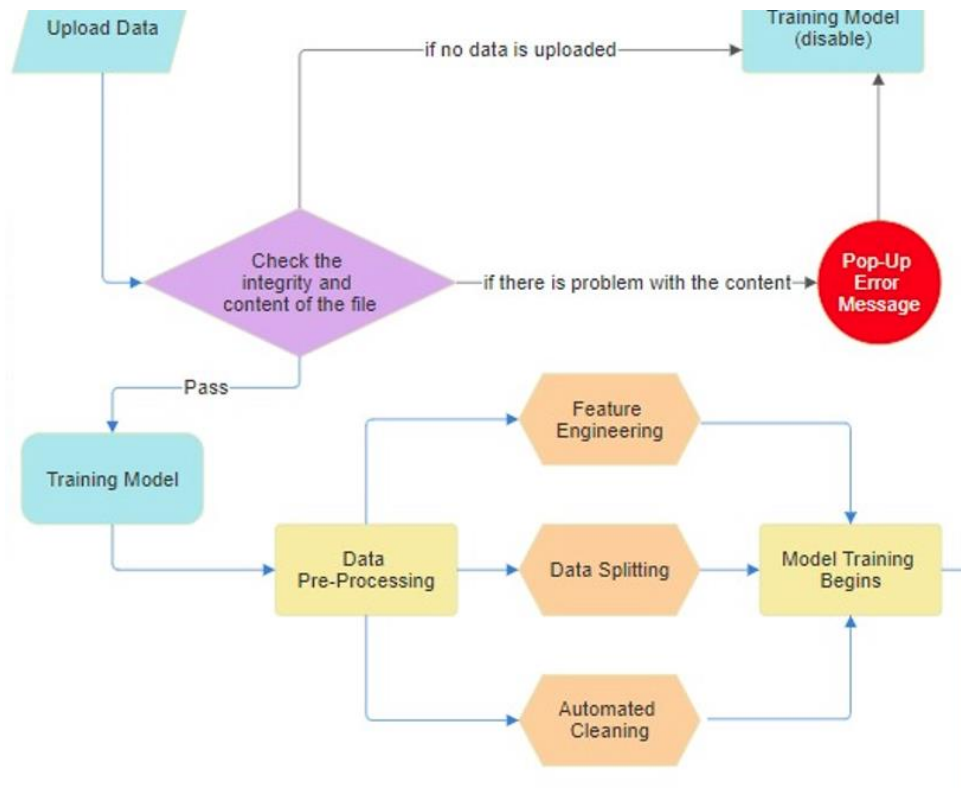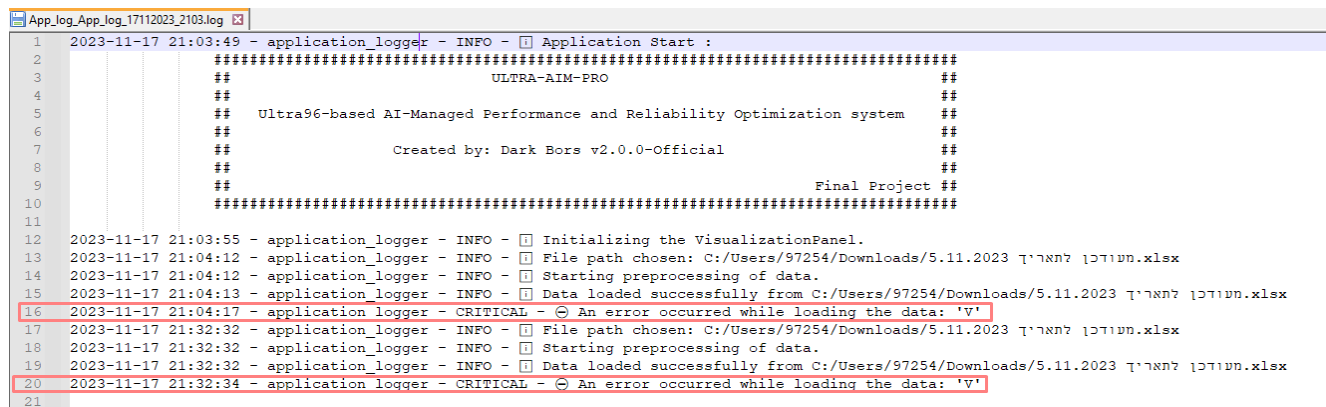
Figure12 :Workflow diagram of the data processing sequence in Ultra Aim Pro. The flowchart illustrates the conditional path from data upload to the initiation of model training, detailing the checks for data integrity, feature engineering, data splitting, and preprocessing steps. It also depicts the system's response when no data is uploaded or if an issue is detected, showing the disabling of the training model function, and triggering of a pop-up error message.

The log indicates that the reliability column was successfully added, and the data was split into training and test sets (see Lines 18 to 22). This is a fundamental step in machine learning, enabling the model to learn from one subset of the data and then be validated against another to prevent overfitting.

Feature Engineering:

The feature engineering process, which is documented in the log, ensures that the neural network receives the most informative features that could significantly impact the model's performance. It's shown that N_squared features were engineered successfully, indicating the system's capability to generate new features that can help improve the model's predictions (as seen in **Error! Reference s ource not found.**on Line 20).

Error Handling and User Feedback:

Figure13 :Screen capture from the Ultra Aim Pro application log showing critical data loading failures, encountering data integrity issues.

In the event of any issues with the data content, the system is designed to provide instant feedback to the user, as showed in the flowchart in **Error! Reference source not found.**. For example, if no data i s uploaded or there is a problem with the data content, the system disables the training model button and alerts the user with a pop-up error message. This mechanism ensures that users are informed of any issues before proceeding with the model training, thus maintaining the integrity of the entire process.

Neural Network Efficiency (SR-4.1.3 and SR-4.1.5):

Parameter Tuning and Model Configuration:

The efficiency of the neural network within "Ultra Aim Pro" was carefully evaluated through a series of parameter tuning exercises. These tests were aimed at determining the optimal configuration that yields the best predictive performance.

- Optimization and Loss Function Configuration:

The model employed the Adam optimizer, renowned for its efficiency in handling thin gradients on noisy problems. The Mean Squared Error (MSE) loss function was chosen for its effectiveness in regression-related tasks, which aligns with the aim of achieving precise numerical predictions.

- **Model Initialization and Parameter Selection:**

The neural network was initialized with a specified input shape and architecture, including the number of dense layers and neurons per layer, as dictated by the complexity of the dataset and the feature space.

Performance Analysis and Validation Results:

The model's performance, post-tuning, was analyzed by comparing its predictions against a reserved set of validation data. The comparative analysis focused on key metrics such as validation loss and R^2 scores to assess the model's accuracy and predictive power.
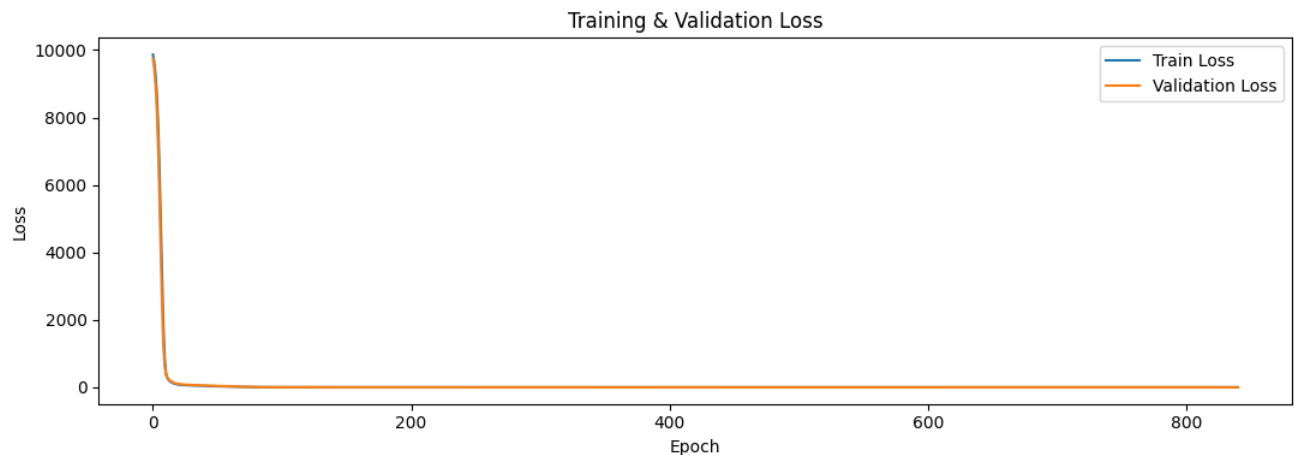
Figure14 : Graphical result of Training and Validation loss over epochs.

In the Model Evaluation phase, the performance of the neural network was quantified using the R^2 score and the Mean Squared Error (MSE) as metrics. The R^2 score, which indicates the proportion of the variance in the dependent variable that is predictable from the independent variables, was found to be 63.4188%. This suggests that the model is able to explain over 60% of the variance in the target variable, which is a substantial amount considering the complexity of the data and the limitations of the dataset size.

Additionally, the MSE, a measure of the average squared difference between the observed actual outturns and the values predicted by the model, was recorded at 0.0469, a metric that quantifies the average squared difference between the predicted and actual values.

This low MSE value suggests a high degree of accuracy in the model's predictions, especially considering the complexity of the data it was trained on.

When compared against a previously higher MSE (as illustrated in the pop-up screenshot from earlier stages of the development), this improvement highlights the effectiveness of the model's tuning and the potential for its application in real-world scenarios. This level of precision in the predictions is promising for the project's aims and signifies a successful application of the neural network to the task at hand. This section of the report underlines the importance of neural network parameter tuning in achieving a model that is not only accurate but also generalizes well beyond the training data. The performance analysis validates the network's efficacy, with the R^2 score serving as a benchmark for the predictive quality of the model.
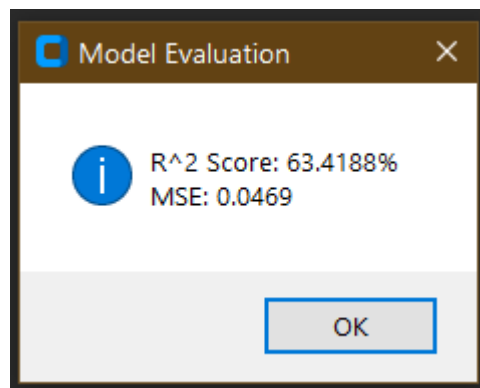
Figure15 :Pop-up dialog box showing the model evaluation metrics with an R² Score of 63.4188%, denoting the proportion of variance explained by the model, and an MSE of 0.0469, reflecting the average squared difference between the predicted and observed values.

Real-Time Monitoring and Feedback (SR-4.1.6):
Overview of performance monitoring tools and real-time feedback mechanisms.

Interpretation of the monitoring data and system's responsiveness to user inputs during training.
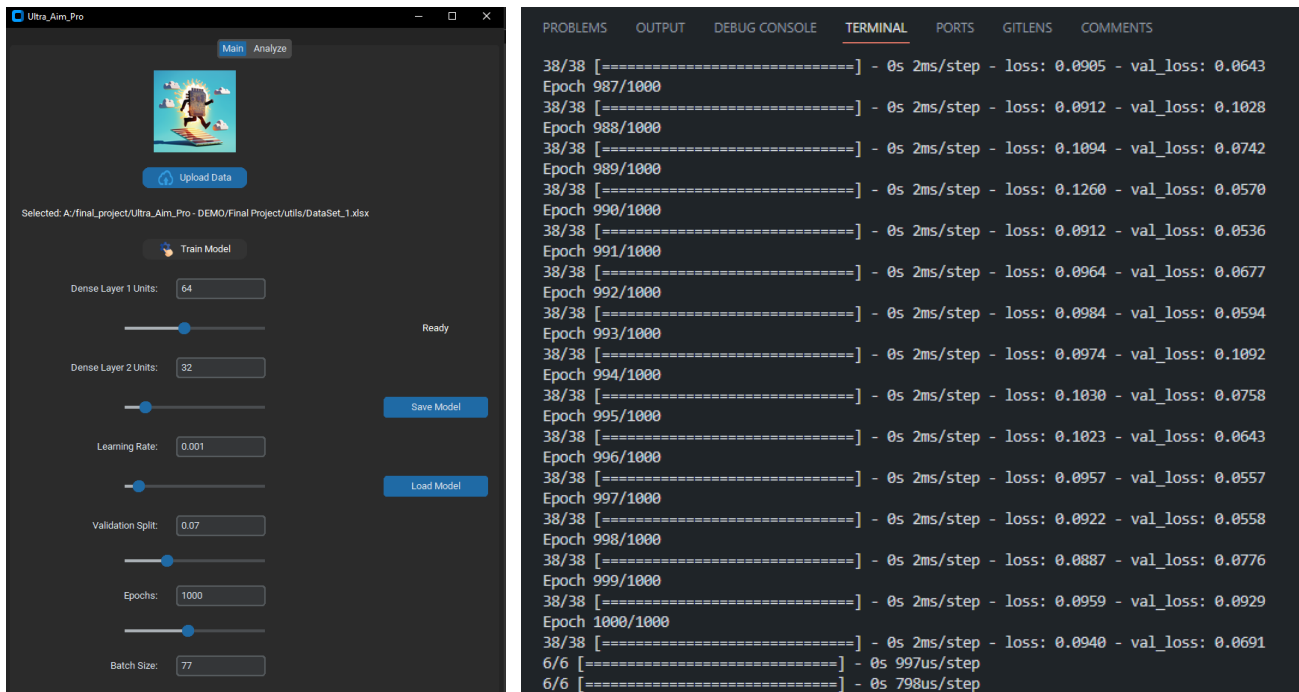
Figure16 :The Main Interface of the app showcasing model configuration options (left) and real-time epoch training progress with loss metrics (right), demonstrating the application's responsive feedback system during the model training phase.

Result Interpretation and Model Accuracy (SR-4.1.7):

Breakdown of result analysis methodologies and the model's accuracy visualization.

Insight into the R^2 score achievement, including the analysis of the score's relation to dataset comprehensiveness. The evaluation of the model's accuracy involved an exact analysis of various performance metrics, crucial for substantiating the reliability of the "Ultra Aim Pro" application.

- **Training & Validation Loss (Figure 1):**
  - ‹ Trend Analysis: The training loss significantly decreased from a starting point of 9867.0635 to 0.0698, while the validation loss similarly reduced from 9744.6494 to 0.0947 over 841 epochs.
  - ‹ Mathematical Insight: The Mean Squared Error (MSE), represented as
    $MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$, was the guiding metric, where **N** is the number of samples, y_i are the true values, and $\hat{y}_i$ are the predicted values by the model.
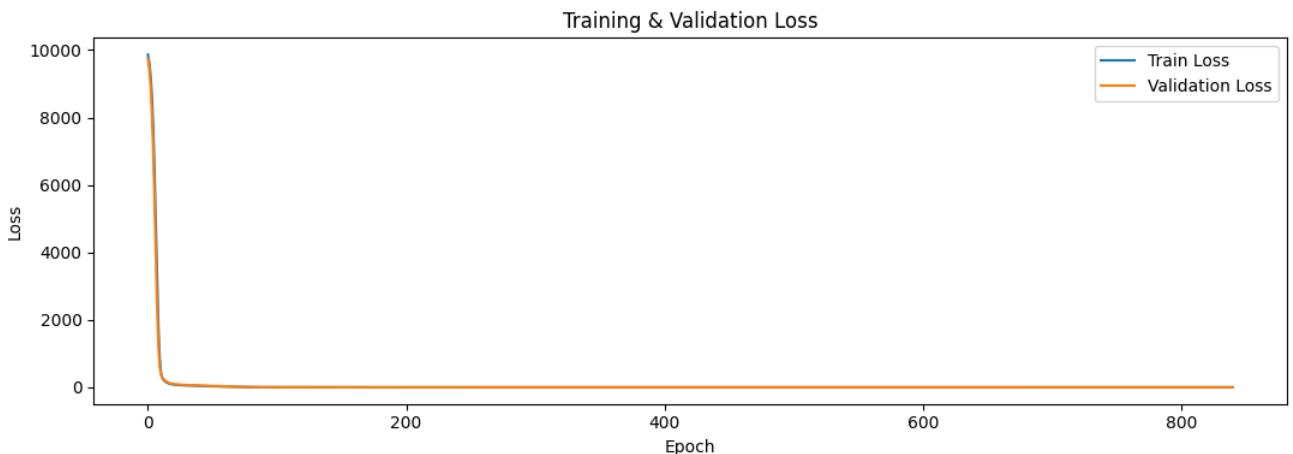
Figure17 :Representing the reduction in training and validation loss, indicative of the model's improved predictive performance over epochs.

~ 33 ~

- **Prediction Accuracy (Figure 2):**
  - ‹ Correlation and Determination: The model's predictions demonstrated a strong Pearson's correlation coefficient (R) of 0.81, emphasizing the strength of the linear relationship with the actual values. Correspondingly, the coefficient of determination (R^2), extracted from the model evaluation snapshot, at 63.4188% underlines that over 63% of the variance in the target variable is predictably captured by the model.
  - ‹ MSE Validation: The model's MSE at 0.0469 validates the accuracy of the predictions, indicating a high level of precision and a low error rate.
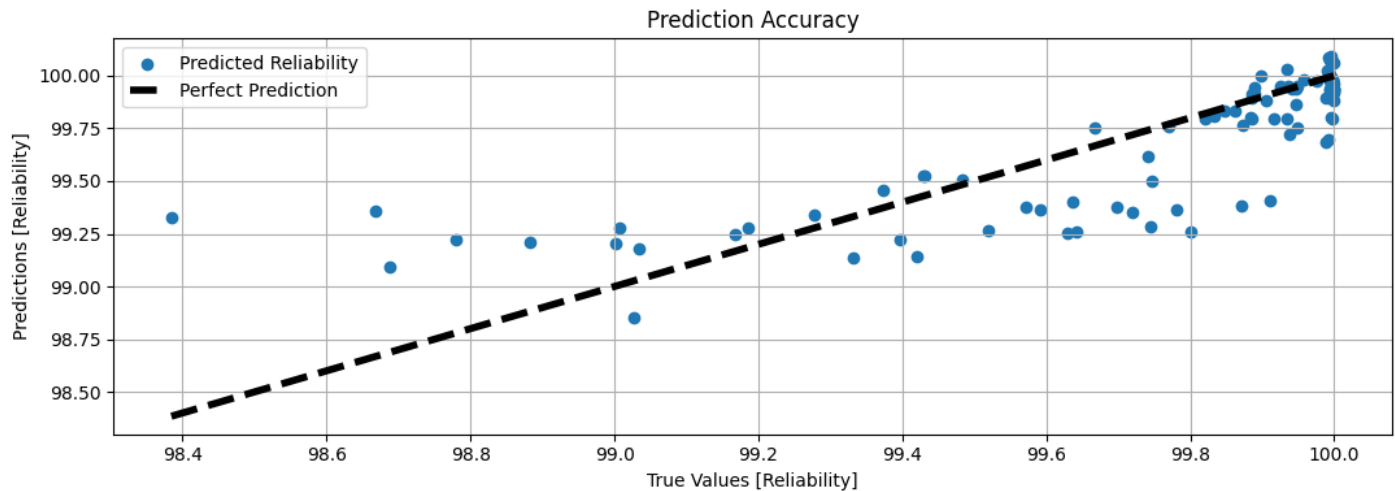
Figure18 :Illustrating the model's accuracy with R and MSE values, reinforcing the validity of the predictive capabilities.

Feature Impact on Predicted Reliability (Figure 3):

- ‹ Influential Features: The impact analysis for individual features revealed varying levels of influence on the predicted reliability, with the correlation coefficients providing quantitative measures of the linear relationships.
- ‹ Statistical Measures: The Pearson's correlation coefficients for features 'N', 'V', 'f', and 'T' were calculated as $r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$, showing how each feature's variability relates to the variability in system reliability.

~ 34 ~
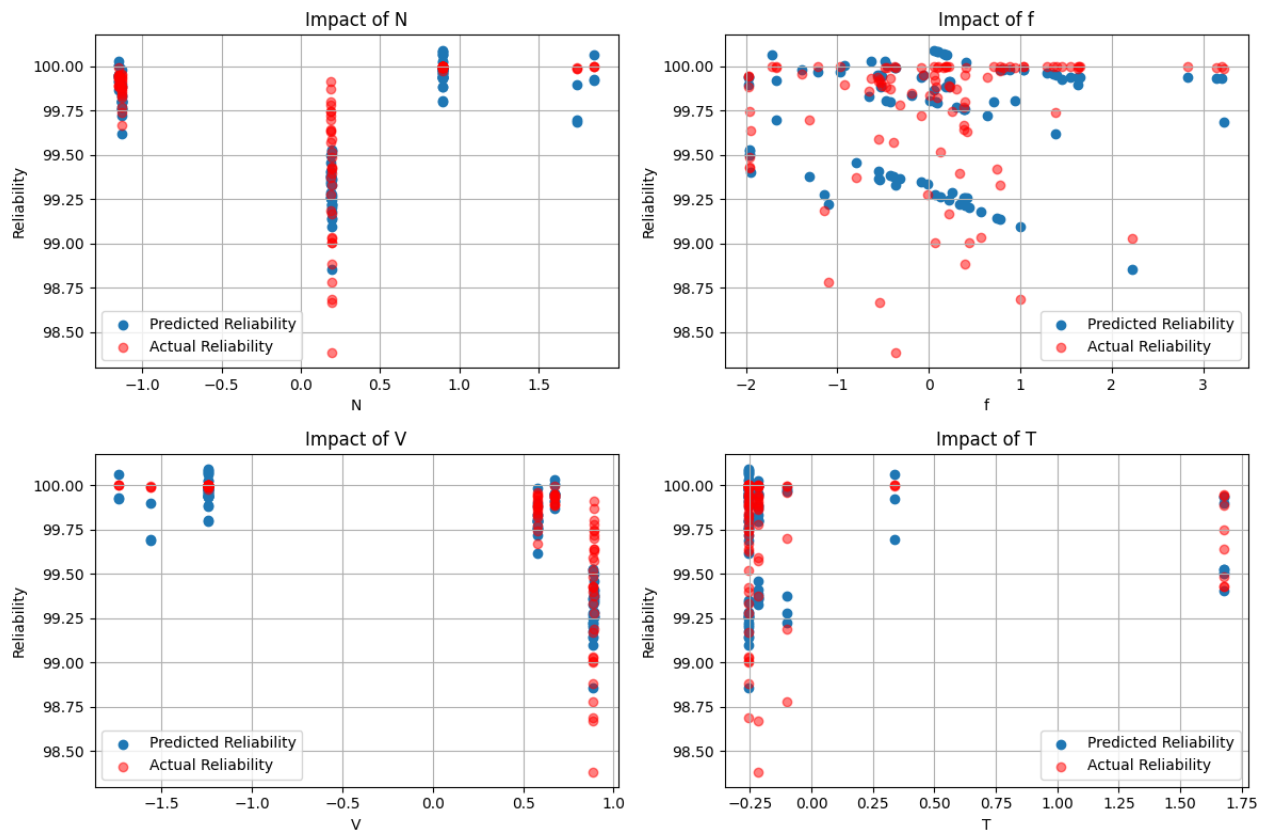
Figure 19:Detailing the impacts of features ('N', 'V', 'f', and 'T') on system reliability, with correlation coefficients highlighting the degrees of influence.

Report Generation and Export Efficacy (SR-4.1.8 and SR-4.1.9):

The effectiveness and user experience of the report generation and data export functionalities in the "Ultra Aim Pro" software are paramount for practical use and knowledge dissemination.

Report Generation Functionality:

‹ **Comprehensiveness**: The automated reports generated by the system provide a holistic overview of the model's performance, including predictive accuracy and loss metrics over training epochs. They serve as essential documentation for model validation and further analysis.

‹ **Inclusion**: Each report should include explanations of the metrics used, such as R² score and MSE, along with visual representations of the data.

Export Features:

‹ **User-Friendliness**: The export feature is designed to be intuitive, allowing users to effortlessly download the trained model, graphs, and analytical reports for use outside the "Ultra Aim Pro" environment.

‹ **Reliability**: Validation of this feature ensures the integrity of exported data, maintaining the fidelity of information across different formats.

‹ **Format Support**: Supports various output formats like .png for graphs, .doc for reports, and .mat files for further analysis, especially using tools like MATLAB for in-depth examination.
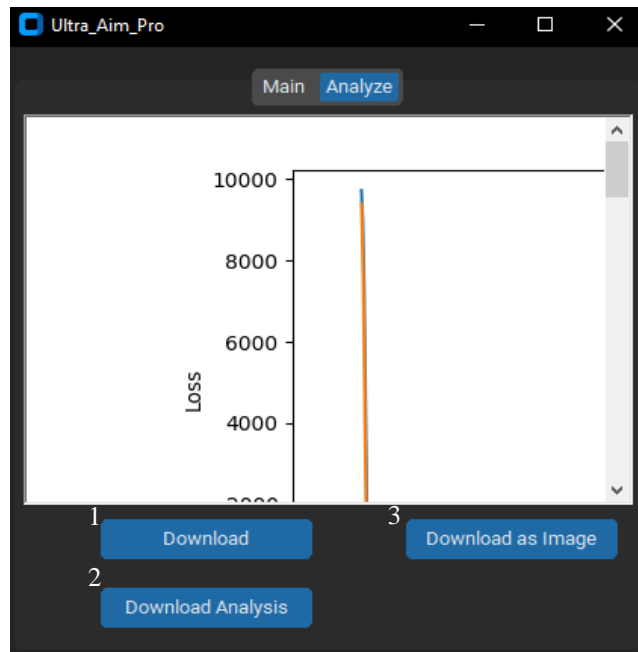
Figure20 : Export interface of Ultra Aim Pro, with download options for MATLAB data (1), detailed analysis report (2), and crucial model performance figures (3).

6.2.Key Takeaways and Project Insights

6.2.1. Overcoming Challenges:

Diving into the development of the UltraAim Pro project, I faced challenges across several key areas, each demanding a unique set of solutions. From tackling software bugs that misaligned data formats, to addressing the details of data processing that risked model accuracy. Optimizing system performance to eliminate latency and ensure responsiveness, difficult validation and testing to uncover hidden bugs, and refining the user interface for a whole experience were all critical steps. Here are the crucial challenges encountered:

Software and UI Defects:

➢ **Issue #1: Coding Errors and GUI Alignment**

Encountered numerous coding and logical errors, particularly in aligning GUI graphs with their frames, demanding extensive effort to rectify initial code issues.

➢ **Root Cause**

A primary factor was disorganized coding practices, stemming from a lack of comprehensive planning. Initial code development was done on an extensive single page, based on a high-level algorithmic concept without detailed architectural planning, leading to recurring errors and logical discrepancies as new features were developed.

➢ **Resolution Approach**

The coding was temporarily halted to reassess and strategize. I began with creating a mind map to delineate the application's main and secondary features. This was followed by defining precise "Software Requirements," setting a clear development path. Essential steps included planning the project's architecture (illustrated in Figure 22) and developing a flow chart for the application process (shown in Figure 6), ideally to be completed prior to code implementation. This structured approach significantly mitigated subsequent errors, rendering them minor and manageable.

➢ **Issue #2: Lack of Real-Time Feedback in User Interface**

The user interface lacked mechanisms for providing real-time updates or accurately reflecting the system's current state, leading to user uncertainty about operations' success or failure.

➢ **Root Cause**

The main issue stemmed from the absence of direct, instantaneous feedback within the UI, preventing users from understanding the system's real-time status. This gap in communication made it challenging for users to navigate the application effectively or trust in its reliability.

➢ **Resolution Approach**

To address this, I implemented a dual solution focusing on enhancing UI responsiveness and establishing a robust logging system for debugging and monitoring. A log file was introduced to capture every step of the system's operation, providing a detailed account for debugging purposes. Simultaneously, the UI was refined to include dynamic elements that better represent the system's current status and data, ensuring users receive immediate and clear feedback on their actions. This comprehensive approach significantly improved the application's usability and user confidence.

Data Processing and Analysis:

➢ **Issue #3: Challenges in Handling FPGA Output for Data Preprocessing**

The core issue revolved around the format and quality of the raw data obtained from the FPGA output. Presented in a .txt file, the data was filled with inconsistencies, such as an excess of NaN values and irregular spacing. These irregularities complicated the initial attempts at cleaning and organizing the data, posing a significant barrier to preparing a clean, usable dataset for further processing and analysis.

➢ **Root Cause**

The initial dataset received from the FPGA output was in a .txt format, presenting significant challenges in data handling. The text files contained numerous NaN values and inconsistent spacing, resulting in a disorganized dataset that was difficult to clean, organize, or filter effectively, causing crucial information loss.

➢ **Resolution Approach**

To avoid these issues, I picked a strategic modification by converting the .txt files into Excel format. This conversion facilitated a more structured approach to data analysis, ensuring data integrity and consistency. Additionally, I recommended that future FPGA outputs be directly provided in an Excel document to streamline the preprocessing phase.

➢ **Issue #4: Ensuring Data Integrity for Machine Learning**

Upon converting the raw FPGA output data into Excel format to enhance manageability, I was challenged with the task of accurately searching through the dataset. The objective was to refine the data for the neural network's training process without succumbing to overfitting or allowing the pitfalls of an imbalanced dataset to skew predictions. This step was critical, as ensuring the integrity and balance of the dataset was significant for the accuracy and reliability of the machine learning model's outputs.

➢ **Root Cause**

Following the data conversion to Excel, the large amount of data required difficult filtering, fixing, and manipulation to tailor the dataset for effective model training. The challenge was to refine the data without introducing overfitting or bias from imbalanced datasets.

➢ **Resolution Approach**

First, I established a specific Software Requirement (SR-4.1.4) focusing on Feature Engineering and Preprocessing, highlighting the need for a systematic data preparation process. Secondly, I thoroughly planned the data integrity and preprocessing steps, as represented in the flow chart (Figure 6). Implementing these steps in the `preprocessing.py` script, I ensured the dataset was optimally prepared for training, addressing overfitting and imbalance issues head-on.

System Performance and Optimization, Validation and Testing:

➢ **Issue #5: Enhancing User Experience Through Reduced System Response Delays**

Initially, the project faced challenges with system responsiveness, where updates to the user interface and data display were delayed, negatively impacting the user experience. This was largely due to the initial development setup which relied on hard-coded data within Jupyter Notebook, resulting in minimal user interaction and inefficient data testing and updates.

➢ **Root Cause**

The core of the issue stemmed from the use of Jupyter Notebooks for coding, which constrained user interaction and necessitated manual adjustments for testing model training parameters. The lack of dynamic interaction and the cumbersome process to change and test values led to significant delays and a rigid testing environment.

➢ **Resolution Approach**

The transition to Visual Studio Code marked a pivotal change in the project's development process. This move facilitated enhanced code management and introduced the ability to adjust parameters dynamically, significantly improving the efficiency of user interactions and system responsiveness. By restructuring the development environment, it became possible to incorporate user feedback directly into the model's parameter tuning (as detailed in section 5.1. Test Environment Setup). This shift not only improved the user experience but also underscored the importance of user engagement in refining model parameters, as established by the modifications discussed in SR-4.1.3 and illustrated in Figure 16.

➢ **Issue #6: Achieving Real-world Scenario Simulation**

The project initially struggled with replicating real-world conditions accurately during testing phases. This challenge was primarily due to the initial reliance on basic neural network algorithms with Sigmoid activation functions, which failed to produce meaningful results, indicating a significant overestimation of the system's robustness and reliability.

➢ **Root Cause**

The initial approach utilized a simplistic algorithm that inadequately addressed the complexity of the data set, resulting in poor model performance. The attempt to normalize the data set with a basic Sigmoid function and without considering the complexity of the data set's dynamics was flawed. This approach was further hampered by the absence of advanced feature engineering techniques that could enhance the model's ability to learn from the data.

➢ **Resolution Approach**

In the initial stages, my approach with a basic neural network and Sigmoid activation function yielded suboptimal results, with R^2 scores close to zero or even negative. Recognizing the limitations of this approach due to the dataset's complexity, I persisted with the Sigmoid function but introduced a strategic enhancement through feature engineering. Inspired by insights from the15article, I incorporated a feature based on the square of dynamic logics (N^2). This modification marked a significant turning point, eliminating negative outcomes, and pushing the results closer to a positive direction.

Further analysis and adjustments were necessary to refine the model's performance. Shifting from Sigmoid to the ReLU activation function aligned more closely with the model's requirements, offering a better framework for training. Additionally, I implemented another layer of feature engineering by incorporating a calculation of reliability in percentage terms. This decision was rooted in a detailed exploration of algorithm design and implementation strategies, as discussed in section 4.2 of the report.

These methodical changes and enhancements were not arbitrary, they were critical steps towards improving model accuracy. Through iterative testing and parameter adjustments, the model's accuracy improved significantly, eventually reaching up to 63%.

This journey through the development and refinement process highlighted the dynamic relationship between data, algorithmic adjustments, and the continuous quest for enhanced accuracy. It reinforced the importance of adaptability in model training, the strategic use of feature engineering, and the critical role of data in shaping model outcomes.

➢ **Issue #7: Simplifying Test Automation for Complex Systems (for future development)**
Automating tests for a project involving complex interactions between hardware and software components proved challenging. This complexity underscored the necessity for advancing testing strategies to achieve comprehensive coverage and ensure system reliability, especially in scenarios that taking place in real-world applications.

➢ **Root Cause**
The complexity characteristic in automating tests for a system with detailed hardware-software interactions was the primary challenge. This complexity made it difficult to create tests that could effectively simulate real-world conditions and provide reliable feedback on the system's performance and endurance.

➢ **Resolution Approach**
Future development efforts will focus on integrating the ULTRA AIM PRO with FPGA logic to automate adjustments based on predictive models.
Expanding the dataset and refining parameter values will be key to approaching the goal of 100% accuracy.
The project was uploaded to Dark-Bors. (2024). Final_ULTRA_AIM_PRO. GitHub repository. Last updated 16/03/2024.
Retrieved from https://github.com/Dark-Bors/Final_ULTRA_AIM_PRO, this invites collaboration, aiming to extend its capabilities and applicability in real-world scenarios. This approach underlines the importance of open collaboration, straightforward project structure, and the adaptability of the UI, analysis, and codebase for future enhancements.

6.2.2. Acquired Skills and Knowledge:

Throughout the development of the UltraAim Pro project, my expertise in Python programming was extensively advanced. This project facilitated a deep dive into GUI development with Tkinter, creating a user interface that was not only functional but intuitive. Implementing the login system improved my skills in user authentication and form handling, critical for ensuring secure and user-specific interactions with the application.

Delving into system architecture, I programmed complicated components that collectively formed the backend of the application, handling data processing, system logging, and neural network operations. I crossed complex libraries and frameworks for data visualization, crafting insightful plots that clarify underlying data trends and model performance metrics.

I also gained practical experience in designing neural networks in Python, leveraging libraries for constructing, training, and evaluating models. The project's success hinged on careful data preprocessing, where I learned the art of transforming actual raw data into a format suitable for machine learning, an essential step for accurate predictive analytics.

Delving into the depths of system engineering, I developed a robust approach to crafting System Requirements (SRs), a process which was crucial for the structured development of the project. This aspect alone vastly improved my ability to foresee system needs and design solutions accordingly. It underscored the importance of integration—melding hardware and software, data flow management, and validation into a coherent, functional system.

Conducting extensive research was a cornerstone of my project, enabling me to explore and implement advanced technologies independently. This deep dive into research cultivated resilience and resourcefulness that were vital in surmounting project hurdles. The journey, though solitary, was replete with learning that enhanced not just my technical acumen but also my soft skills. Self-management, critical thinking, and self-reliance were continually refined as I navigated the project's lifecycle, from ideation to fruition.

6.3. Overall Project Summary

The Overall Project Summary of "UltraAim Pro" encapsulates the essence and achievements of this pioneering final year project in Electrical and Electronic Engineering (EEE). "UltraAim Pro" represents a significant leap in computational device optimization, adeptly balancing performance with long-term reliability through the innovative use of artificial intelligence. At the heart of the project lies a custom-developed neural network, crafted on the Ultra96 platform, which dynamically adjusts operational parameters in real-time, ensuring devices operate at their peak without compromising durability.

This project involved extensive Python programming, GUI development utilizing Tkinter, and the integration of complex libraries for data visualization and neural network operations. It faced and overcame numerous challenges, including software and UI defects, through meticulous planning and structured development.

Test analyses and system performance evaluations confirmed the effectiveness of "UltraAim Pro," showcasing its robustness under varied conditions and its potential in predictive maintenance and performance optimization. The project outlines plan for future enhancements, including comprehensive testing, efficiency improvements, and feature expansion, emphasizing its adaptability to evolving technologies.

"UltraAim Pro" has set a new benchmark in AI integration for performance and reliability optimization in computational devices, promising not only enhanced operational efficiency and hardware longevity but also paving the way for future innovations in the field.

7. Appendix

7.1. Appendix A: Dataset Used for the Module

Table 2: Representative Sample of Dataset for UltraAim Pro Project. This table showcases a subset of the original data, providing five sample entries for each distinct value of 'N'. The selected 'N' values include 3, 5, 11, 101, 33, and 333, demonstrating the dataset's diversity and the range of conditions under which the system was evaluated.

N	f	V	T	ttf
3	1.27E+09	0.820749	112.5442	8.81E+08
3	1.27E+09	0.820749	112.5442	8.81E+08
3	8.73E+08	0.820749	112.5442	1.79E+09
3	7.04E+08	0.820749	112.5442	1.21E+09
3	7.57E+08	0.820749	112.5442	7.27E+09
3	5.28E+08	0.820749	112.5442	1.17E+09
5	6.08E+08	0.820749	112.5442	1.41E+09
5	5.63E+08	0.820749	112.5442	2.07E+09
5	5.6E+08	0.820749	112.5442	2.41E+09
5	6.2E+08	0.820749	112.5442	3.53E+09
5	5.09E+08	0.820749	112.5442	6.37E+09
11	2.79E+08	0.820749	112.5442	1.36E+09
11	2.85E+08	0.820749	112.5442	5.65E+08
11	2.13E+08	0.820749	112.5442	1.52E+09
11	2.84E+08	0.820749	112.5442	1.95E+09
11	2.89E+08	0.820749	112.5442	4.32E+09
101	33405640	0.820749	112.5442	1.64E+09
101	28647310	0.820749	112.5442	1.58E+09
101	29402780	0.820749	112.5442	1.48E+09
101	29828330	0.820749	112.5442	1.51E+09
101	29591900	0.820749	112.5442	1.63E+09
33	1.28E+08	1.244	-24.74	1.79E+10
33	1.33E+08	1.244	-24.74	1.73E+10
33	1.34E+08	1.244	-24.74	1.2E+10
33	1.32E+08	1.244	-24.74	1.1E+10
33	1.31E+08	1.244	-24.74	1.53E+10
333	13612238	1.244	-24.74	1.54E+10
333	13509584	1.244	-24.74	1.36E+10
333	13556231	1.244	-24.74	1.26E+10
333	13538699	1.244	-24.74	1.58E+10
333	13401185	1.244	-24.74	1.39E+10
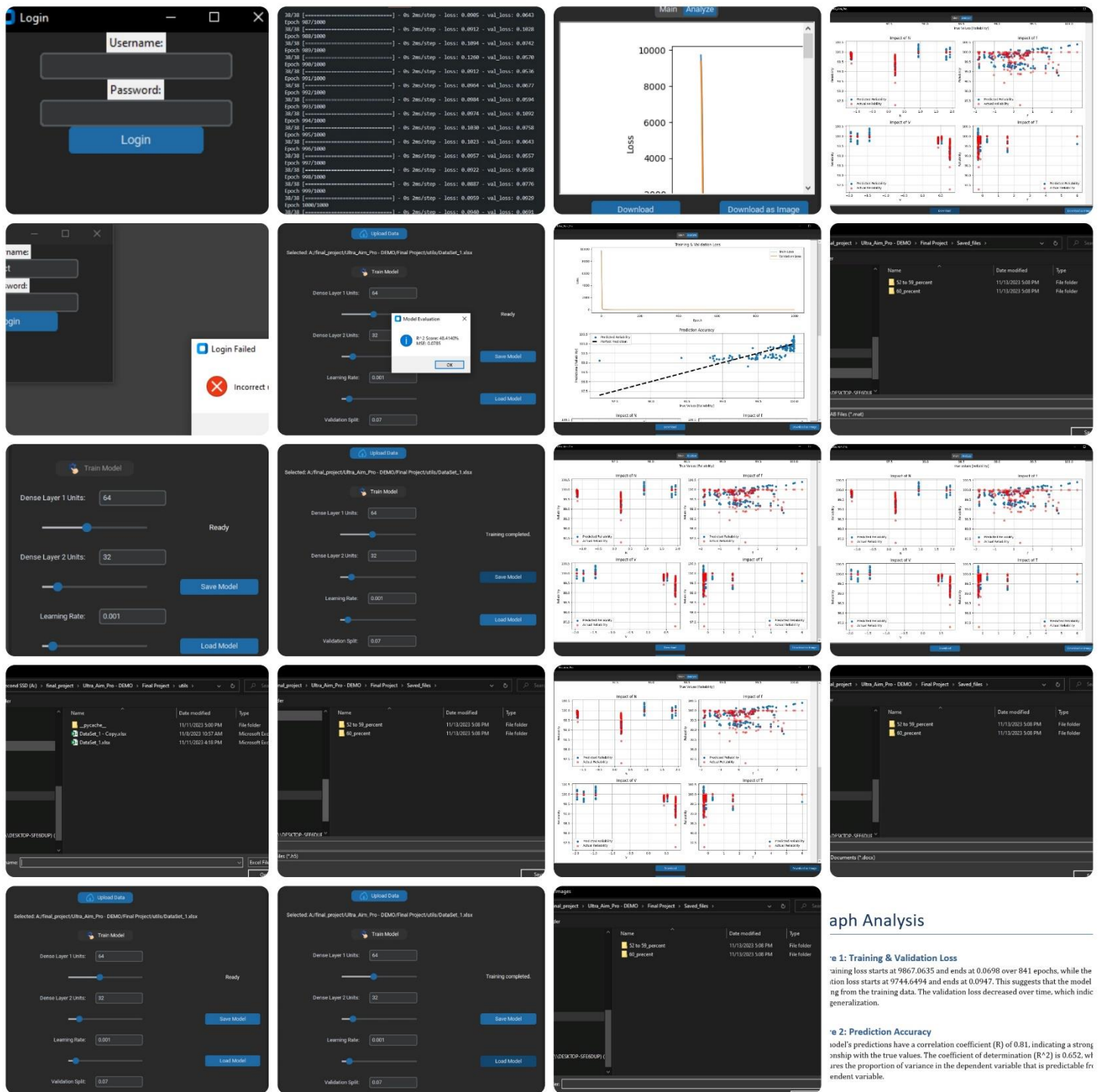
Figure21 : Sequential Screenshots Illustrating the Workflow of the UltraAim Pro Application. The process begins with the login screen (top left) and proceeds vertically down, showcasing various operational stages such as model configuration, system training, performance evaluation, and result visualization. The sequence continues in the adjacent column starting from the top, highlighting the system's interactive features and analytical capabilities, ultimately providing a user-friendly experience and in-depth system analysis.

7.3.Appendix C: Architecture of the ULTRA AIM PRO Application

```
Final_ULTRA_AIM_PRO/
|
├── main.py - Entry point to initialize and run the application.
├── app_logging.py - Handles the logging mechanism of the application.
├── requirements.txt - Lists all dependencies for the project.
├── Run_Main_App.bat - Batch script to run the application on Windows.
|
├── data/ - Contains datasets and data-related scripts.
|
├── gui/ - Houses the graphical user interface components.
|   ├── login_page.py - Manages the login interface.
|   ├── main_window.py - The main application window.
|   └── visualization_panel.py - For data visualization controls.
|
├── utils/ - Utility scripts for general functionalities.
|   └── utilities.py - Miscellaneous utility functions.
|
├── model/ - Neural network models and training scripts.
|   └── neural_network.py - Implementation of the neural network.
|
├── graphics/ - Graphical assets used across the application.
|
├── temp/ - Temporary files during execution.
|
└── saved files/ - Output and serialized models are stored here.
```

Figure22 : An overview of the ULTRA AIM PRO Application file structure, meticulously organized for optimal performance and ease of navigation, showcasing the backend and frontend components.

8. Reference Materials

8.1. List of Tables

8.2. List of figures

9. Bibliography

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