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Original Article

Integrating Low-Cost Mini CNC Machines with IoT-Enabled Energy Monitoring and Machine Learning for Sustainable Manufacturing

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Abstract - *This research investigates the integration of low-cost mini CNC machines with the Internet of Things (IoT)-enabled energy monitoring and machine learning techniques to enhance sustainable manufacturing practices. Through meticulous mechanical, electronic, and software design, a mini CNC machine based on the ESP8266 platform is developed, enabling comprehensive data acquisition and analysis of energy consumption patterns during machining processes. Leveraging machine learning classification techniques, including Logistic Regression, K-Nearest Neighbors, Support Vector Classification, Decision Trees, Random Forest, Gradient Boosting, and AdaBoost, Gradient Boosting emerges as the most effective approach for energy consumption prediction in mini CNC operations, showcasing notable accuracy and robustness. By providing insights into energy efficiency and sustainability in manufacturing, this research contributes to the ongoing discourse on sustainable practices and lays the groundwork for further advancements in CNC technology and education. This integration offers a practical solution to the challenges of accessibility and affordability in CNC education and small-scale manufacturing, giving a solution for the broader adoption of sustainable manufacturing practices in various industrial settings.*

Keywords - *Mini CNC machines, Internet of Things, Energy monitoring, Machine Learning, Sustainable manufacturing.*

1. Introduction

Computer Numerical Control (CNC) devices, which provide unmatched accuracy and efficiency in manufacturing processes, have completely changed the fields of prototype and production [1]. CNC technology has a significant impact on how the engineering and manufacturing sectors will develop in the future, both in industrial applications and educational settings [2]. The integration of CNC programming and control competencies into the curriculum, especially for first-year university students, is a considerable barrier despite the technology's extensive application and significance [3].

Because CNC machines are expensive, access to them for educational purposes has historically been limited [4]. This has made it difficult to provide students with practical experience using and programming these machines [5]. This restriction highlights the need for reasonably priced substitutes that can speed up learning without lowering the standard of instruction [6]. A solution to this research gap is the use of mini CNC machines, which provide lower production costs while maintaining necessary features for teaching. Of these options, the ESP8266 microcontroller platform integration seems like a good fit because it is reasonably priced and can be used to teach beginners CNC programming and control concepts [7]. Therefore, in this paper three research objectives are discussed, namely the manufacture of low-cost mini CNC machines, the collection of energy consumption datasets, and the determination of machine learning classification models for energy consumption prediction. This first research aims to create a small CNC machine based on the ESP8266 platform, together with stepper motors, GRBL firmware, Microstep Drivers, and a drilling mechanism, to meet this demand. Testing of mini CNC machines is carried out by printing several specimens by comparing the shape of the CAD model and the printed results. Furthermore, this study supports larger sustainability measures that aim to lower energy use [8], especially in Thailand, outside of the educational sphere [9]. Internet of Things (IoT) technology is used to gather energy usage statistics of the tiny CNC machine in order to support these efforts [10]. This information informs future design and operation improvements and is a useful tool for analysing the energy efficiency of small CNC machines [11]. In order to accomplish this, it is necessary to relate the geometric aspects of the product with the energy usage during manufacture; by focusing on CNC machine tools along with NC codes, energy consumption predictions can be achieved by identifying the specific parts of the machine that are operational or in motion.

Additionally, the gathered energy consumption dataset is examined using machine learning classification techniques to determine which models are most appropriate for this kind of data. This study aims to identify efficient models for assessing and improving energy efficiency in small-scale CNC machining processes by utilising a variety of Machine Learning Classification techniques, including Gradient Boosting, AdaBoost, K-Nearest Neighbours, Decision Trees, Random Forest, and Logistic Regression [12]-[16]. This research advances our knowledge of the performance of tiny CNC machines and adds to the continuing discussion on energy conservation and sustainable manufacturing methods by utilising sophisticated analytical techniques.

2. Research Gap

The integration of low-cost mini CNC machines with IoT-enabled energy data collecting and machine learning techniques for energy consumption prediction is still not well covered in the literature [17]-[19], despite the advancements in miniaturised CNC technology and the growing emphasis on sustainability in manufacturing processes [20][21]. Few studies have specifically addressed the opportunities and challenges presented by low-cost mini CNC machines in combination with IoT technology and machine learning algorithms [22]-[25].

Previous studies have looked into the development of mini CNC machines for educational purposes and energy consumption in conventional CNC operations. Existing research often focuses on either the mechanical design and functionality of mini CNC machines or on energy efficiency in traditional CNC manufacturing settings. However, there is a lack of comprehensive studies that bridge these domains by examining the design, implementation, and performance of low-cost mini CNC machines equipped with energy monitoring capabilities and evaluated using advanced machine learning techniques.

Furthermore, while sustainability in manufacturing has become an increasingly critical concern, particularly in terms of energy consumption reduction, there is limited research that specifically targets the integration of IoT technology and machine learning for optimizing energy efficiency in mini-CNC operations. Understanding how these technologies can be effectively leveraged to monitor and predict energy consumption in mini CNC machines is essential for advancing sustainable manufacturing practices, especially in educational and small-scale production settings.Therefore, this research aims to address this gap by developing a low-cost mini CNC machine integrated with IoT-enabled energy monitoring capabilities and utilizing machine learning algorithms for energy consumption prediction. This study intends to contribute to the current discussion on sustainable manufacturing methodologies and provide insightful viewpoints on the potential of IoT and machine learning to improve energy efficiency in small-scale CNC operations.

3. Research Methodology

3.1. Mechanical Design

In the initial stage, the mechanical design of the mini CNC machine was carried out. The plate holder is moved based on the X and Y axes using two stepper motors. Meanwhile, the Z axis in the form of a drilling machine is driven using a stepper motor which moves up and down. The basic concept of screw sliding is the basis for this mechanical design. This CAD design becomes the basis for making an actual CNC machine.

3.2. Electronic Design

The CNC machine's electronic parts make up an assembly that is essential to both its precision and functionality. The power supply unit, which is at the center of this assembly, transforms AC power into a steady DC supply so that the system is continuously powered. The ESP32 microcontroller acts as the machine's brain, executing control software, interpreting G-code commands, and coordinating the movement of stepper motors along the X, Y, and Z axes.

Microstep drivers ensure precise motor control, while stepper motors translate electrical pulses into accurate motion. The Frenic Mini motor drive unit regulates spindle speed and direction, enhancing cutting and drilling operations' precision. Integrated drilling machinery further expands the CNC system's capabilities, allowing for precise hole creation. Together, these components form a robust and versatile system capable of delivering accurate machining results for various applications.

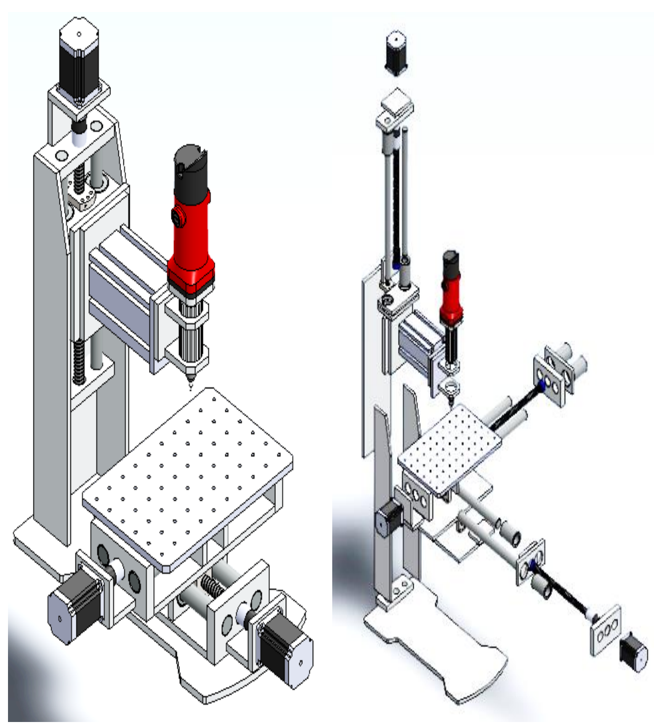


Fig. 1 Hardware CAD design

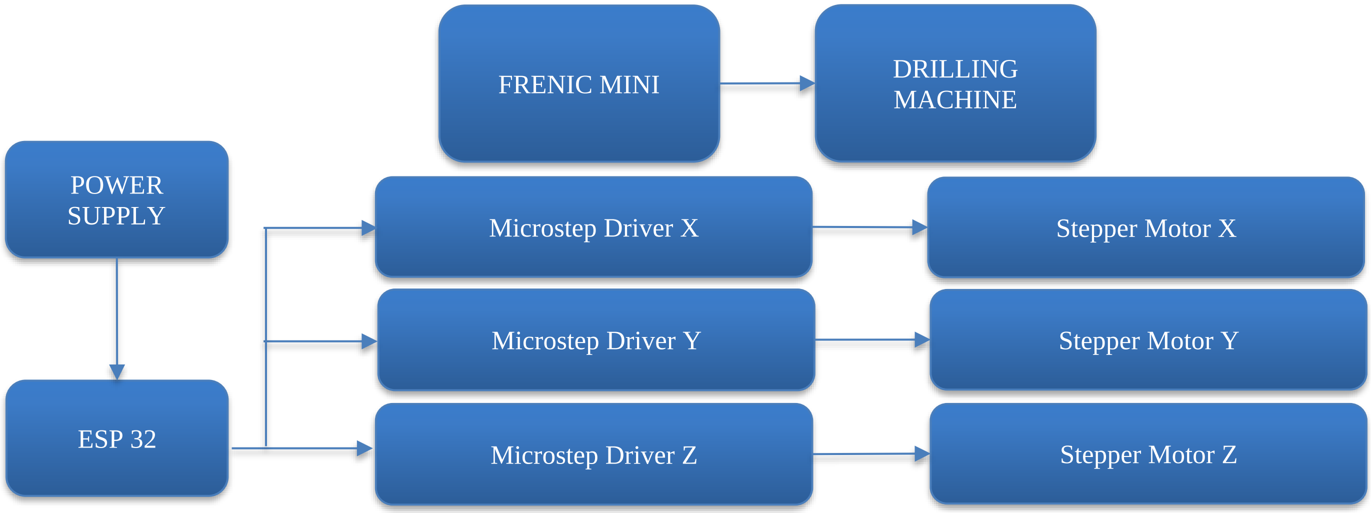


Fig. 2 Electronics component design

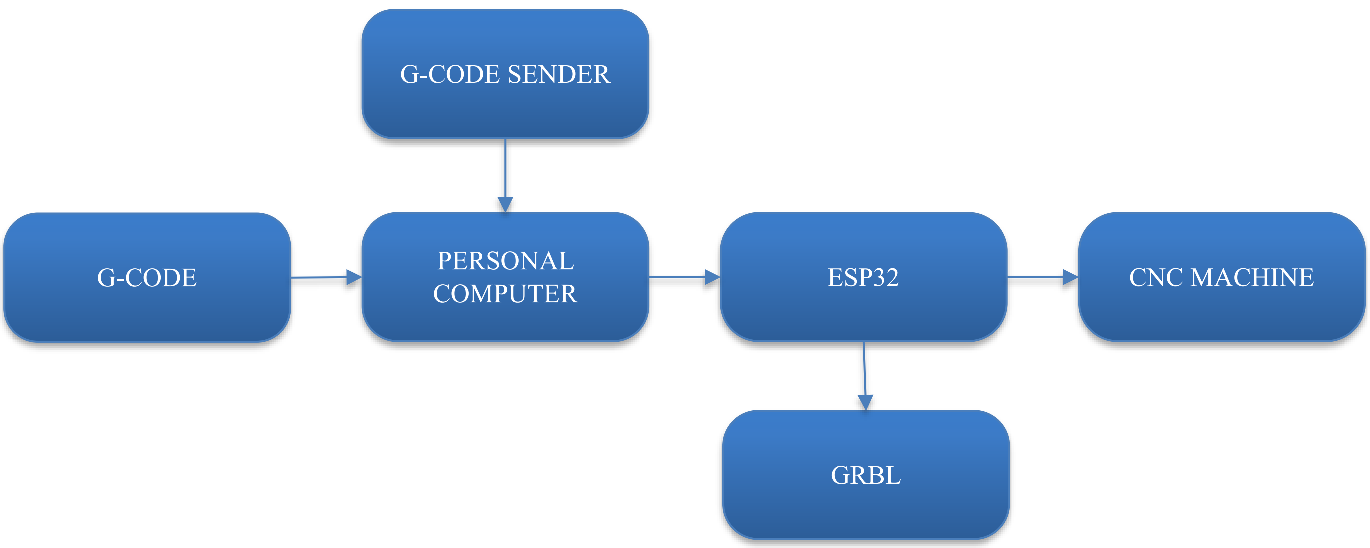


Fig. 3 Software design

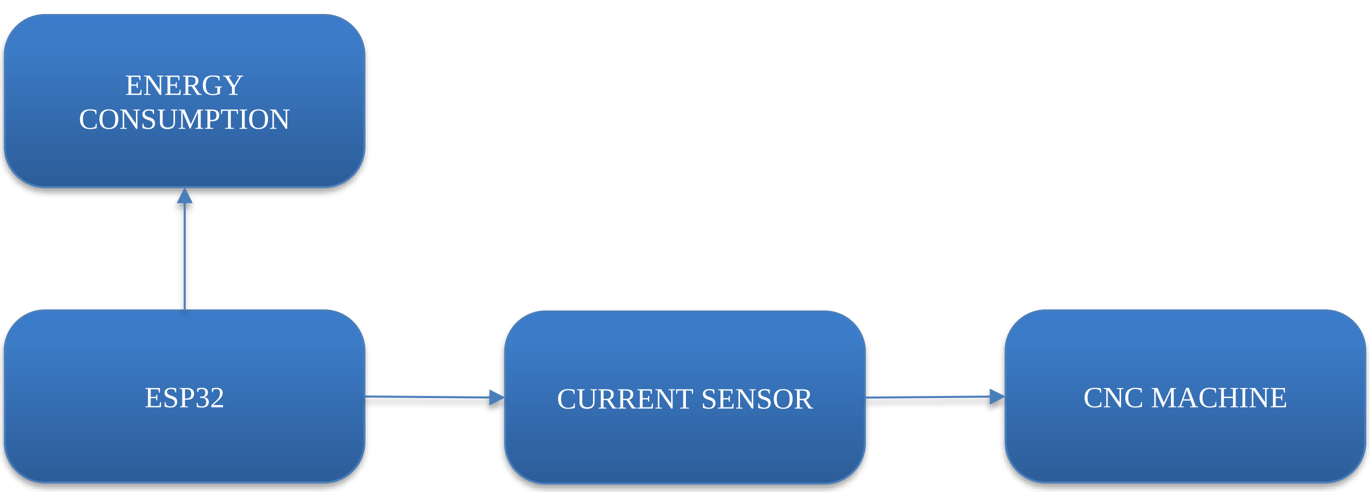


Fig. 4 Data acquisition design

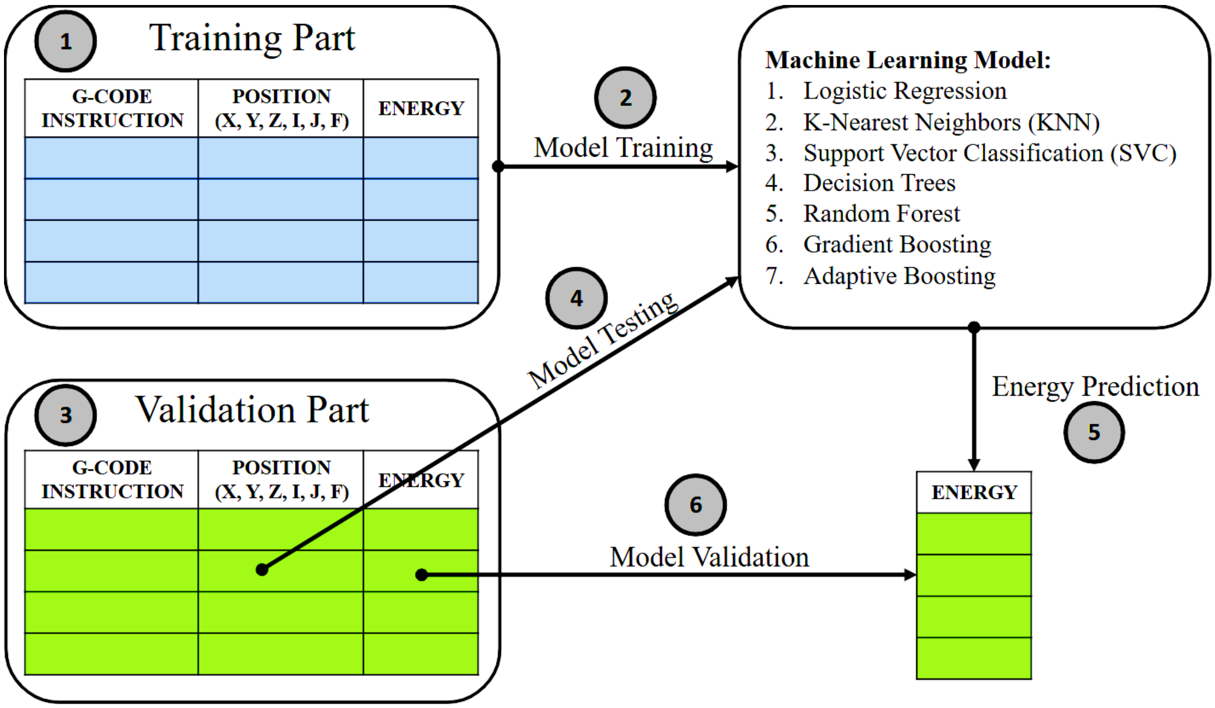


Fig. 5 Machine learning experimental design

3.3. Software

The CNC machine's software orchestrates its operations seamlessly through a structured workflow. It begins with the generation of G-code, a standardized programming language that defines toolpaths and machining instructions. This G-code is then transmitted from a personal computer equipped with a G-code sender application to the ESP32 microcontroller, which runs the GRBL firmware—a specialized CNC control software. GRBL interprets the G-code commands, coordinating the movement of stepper motors and controlling auxiliary functions such as spindle speed and tool changes. Through this efficient communication pathway, the CNC machine executes precise and intricate machining tasks with accuracy and reliability, ensuring seamless translation of digital designs into physical objects.

3.4. Data Acquisition

The CNC machine's data acquisition process is streamlined and precise, facilitating comprehensive monitoring of energy consumption. Embedded within the machine is a current sensor, such as the ACS712, which accurately measures the electrical current flowing through the system during operation. This sensor sends real-time data to the ESP32 microcontroller, acting as the central hub for data processing and analysis. Leveraging its computational power, the ESP32 processes the incoming data and compiles it into a structured energy consumption dataset. By capturing and analyzing this dataset, operators gain valuable insights into the CNC machine's energy usage patterns, enabling informed decision-making regarding efficiency improvements and resource optimization strategies.

3.5. Machine Learning Model

In the training phase, the CNC machine's operations are meticulously recorded, capturing G-code instructions and corresponding positional data encompassing X, Y, and Z coordinates, as well as additional parameters such as I, J, and F values. Various machine learning algorithms mentioned in the introduction section are utilized during model training for this purpose. The model is trained to correlate G-code instructions and positional data with energy consumption patterns, thus enabling the prediction of energy usage during the CNC machining process. In the subsequent validation stage, the trained models are tested using a new set of G-code instructions, positional data, and real-time energy consumption measurements. This validation process ensures the reliability and accuracy of the models in predicting energy consumption based on CNC machine operations.

In our study, we explore a variety of Machine Learning Classification techniques to analyze energy consumption data from the mini CNC machine and inform strategies for optimizing energy efficiency while advancing sustainability goals. Logistic Regression provides fundamental insights into factors influencing energy efficiency by modeling the relationship between input features and binary outcomes of high or low energy consumption.

K-Nearest Neighbors (KNN) identifies patterns in energy consumption data based on similarities between operating conditions, utilizing non-parametric classification and regression tasks. Support Vector Classifier (SVC) discerns distinct energy consumption patterns associated with various

CNC machine settings by mapping input features to a higher-dimensional space and maximizing the margin between different classes. Decision Trees offer interpretability and capture complex interactions among input features, revealing hierarchical relationships between operating parameters and energy consumption.

The Random Forest method reduces overfitting and improves generalization performance by combining results from numerous decision trees, resulting in strong predictions of energy consumption. Gradient Boosting captures subtle relationships between input features and energy consumption by iteratively fitting models to residuals of previous models, resulting in accurate predictions. AdaBoost enhances predictive performance by iteratively refining the model based on misclassified instances, improving overall accuracy. Through rigorous evaluation, we aim to identify the most suitable model for analyzing energy consumption data and optimizing energy efficiency in CNC operations.

3.6. Evaluation

In order to evaluate the small CNC machine's performance, four different pieces were made using two different materials: acrylic and wood. Two wooden pieces' CAD designs are shown in Figure 6, and two acrylic parts are shown in Figure 7. The correctness of the outputs that were created was then evaluated by manufacturing and evaluating these four components using a modified version of the black box testing technique.

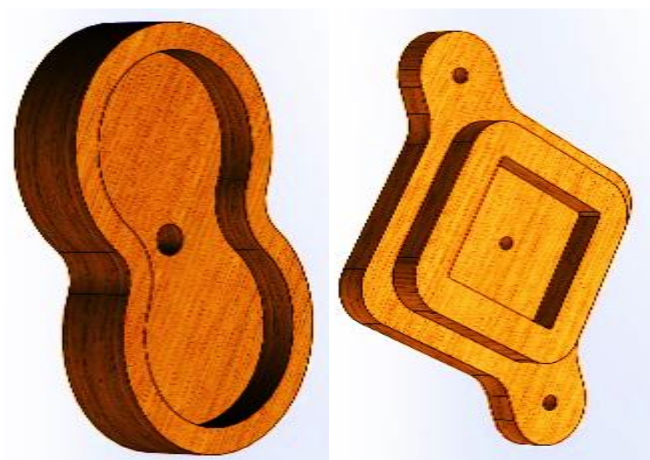


Fig. 6 Wooden CAD part

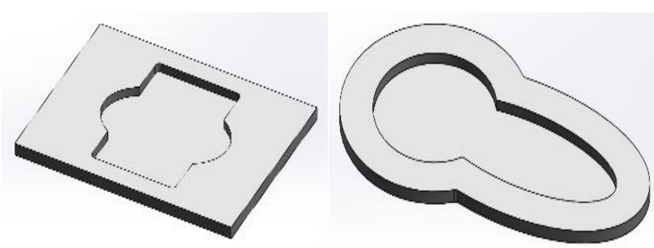


Fig. 7 Acrylic CAD part

A comprehensive evaluation of the Machine Learning Classification models utilized in our analysis, employing a range of performance metrics to assess their effectiveness and robustness in predicting energy consumption patterns in the mini CNC machine. Grouping As a fundamental metric, accuracy measures the proportion of correctly classified cases to the total dataset and offers a broad picture of prediction effectiveness. Precision measures the accuracy of the model's positive forecasts in more detail and is especially important when reducing false positives is the top priority. Recall, also known as sensitivity, assesses how well the model can detect positive examples, which is essential for catching all positive cases and reducing false negatives. A balanced assessment is provided by the F1-Score, a harmonic mean of recall and accuracy that is particularly useful for datasets with an unbalanced class distribution where the importance of false positives and false negatives is similar. By providing a detailed understanding of each model's performance, these metrics enable decision-makers to make well-informed predictions regarding the consumption of CNC operations.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \tag{1}$$

$$Precision = \frac{True\ Positives}{True\ Positives + Flase\ Positives} \tag{2}$$

$$Recall = \frac{True\ Positives}{True\ Positives + Flase\ Negatives} \tag{3}$$

$$F1 - Score = 2 * \frac{Precision\ *\ Recall}{Precision\ +\ Recall} \tag{4}$$

A binary classification model's performance is visually represented by the Receiver Operating Characteristic (ROC) Curve, which plots the true positive rate versus the false positive rate across a range of threshold values. This curve shows how to strike a compromise between specificity and sensitivity. In the meantime, the Area Under the ROC Curve (AUC), which shows the likelihood of ranking a randomly chosen positive instance higher than a randomly chosen negative instance, is used to evaluate the overall performance of the model. A higher AUC value indicates greater discrimination ability across all threshold settings. By assessing each machine learning classification model's classification accuracy, precision, recall, F1-Score, ROC Curve, and AUC, we offer a thorough analysis of how well it can predict patterns of energy usage in the micro CNC. These indicators provide priceless insights into the advantages and disadvantages of the models, making it easier to choose the best strategy for energy efficiency and achieving sustainability goals.

4. Results and Discussion

4.1. Mechanical Assembly

Based on the results of the CAD mechanical design, the assembly of mini CNC machines is carried out, as seen in Figure 8. From this picture, it can be seen that all parts are installed and connected to a box controller. On the controller box, there is an emergency button and an on-off switch equipped with indicator lights.

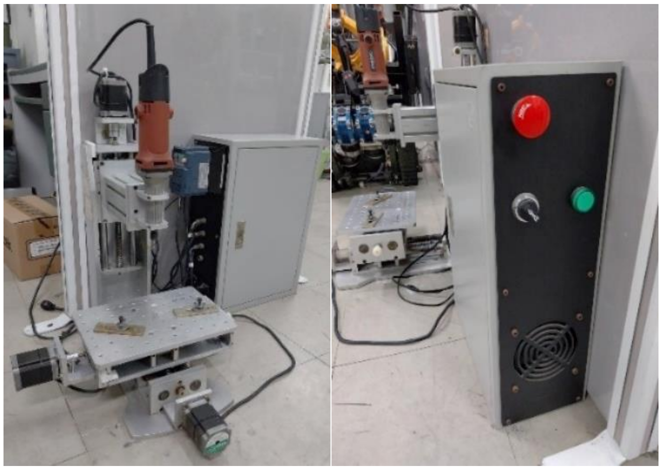
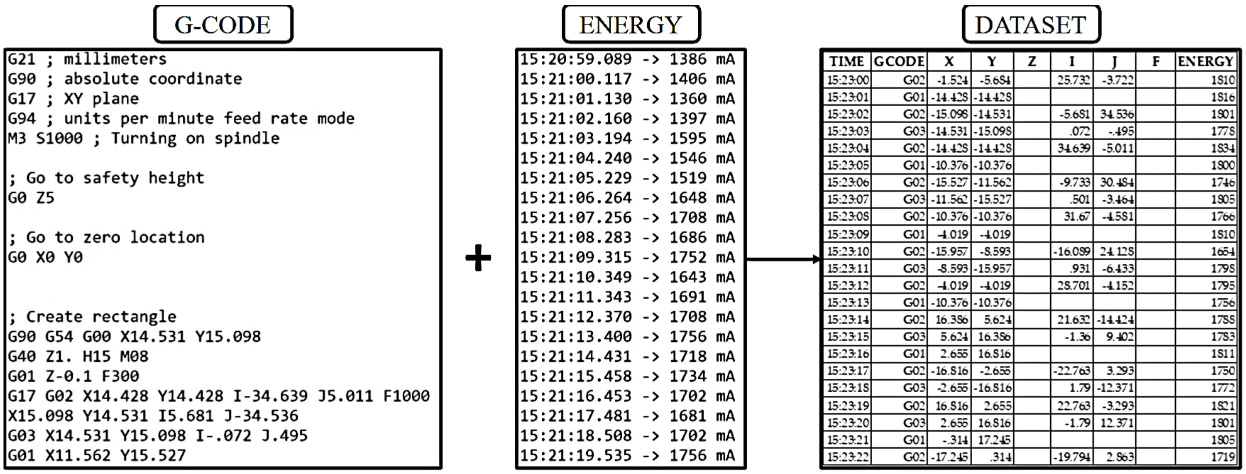


Fig. 8 Hardware assembly

Fig. 9 Electronics assembly



TIME	GCODE	X	Y	Z	I	J	F	ENERGY
15:23:00	G02	-1.524	-5.684		25.732	-3.722		1810
15:23:01	G01	-14.428	-14.428					1816
15:23:02	G02	-15.098	-14.531		-5.681	34.536		1801
15:23:03	G03	-14.531	-15.098		.072	-.495		1778
15:23:04	G02	-14.428	-14.428		34.639	-5.011		1834
15:23:05	G01	-10.376	-10.376					1800
15:23:06	G02	-15.527	-11.562		-9.733	30.484		1746
15:23:07	G03	-11.562	-15.527		.501	-3.464		1805
15:23:08	G02	-10.376	-10.376		31.67	-4.581		1766
15:23:09	G01	-4.019	-4.019					1810
15:23:10	G02	-15.957	-8.593		-16.089	24.128		1654
15:23:11	G03	-8.593	-15.957		.931	-6.433		1798
15:23:12	G02	-4.019	-4.019		28.701	-4.152		1795
15:23:13	G01	-10.376	-10.376					1756
15:23:14	G02	16.386	5.624		21.632	-14.424		1788
15:23:15	G03	5.624	16.386		-1.36	9.402		1783
15:23:16	G01	2.655	16.816					1811
15:23:17	G02	-16.816	-2.655		-22.763	3.293		1750
15:23:18	G03	-2.655	-16.816		1.79	-12.371		1772
15:23:19	G02	16.816	2.655		22.763	-3.293		1821
15:23:20	G03	2.655	16.816		-1.79	12.371		1801
15:23:21	G01	-.314	17.245					1805
15:23:22	G02	-17.245	.314		-19.794	2.863		1719

Fig. 10 Combined dataset

4.2. Electronic Assembly

In Figure 9, you can see the results of assembling the electronic circuit of a mini CNC machine. The MCU node serves as the main controller connected to all three microstep drivers. These three drivers are then connected to three stepper motors that each massively drive the part to be printed based on the X, Y, and Z axes. A current sensor is also installed to record the energy consumption data of CNC machines.

4.3. Data Acquisition

At this stage, data collection has been successfully carried out on four parts that have been printed using a mini CNC machine. This data was initially separated between the G-Code and energy consumption, then interpretation and merging of these two data as seen in Figure 10. The data consists of several Numerical Control (NC) instructions, coordinates (X, Y, Z), several other parameters (I, J, and F), and energy consumption. In Figure 11, you can see the results of plotting the X and Z axes of one of the parts used as model validation. Energy recording is carried out using the ACS712 sensor where the recording results are ampere. Therefore, this result is then converted into Joules by multiplying the energy consumption (Ampere) by 220 V. The results of processing this energy data are presented in Figure 12. Meanwhile, Figure 13 presents the distribution of datasets.

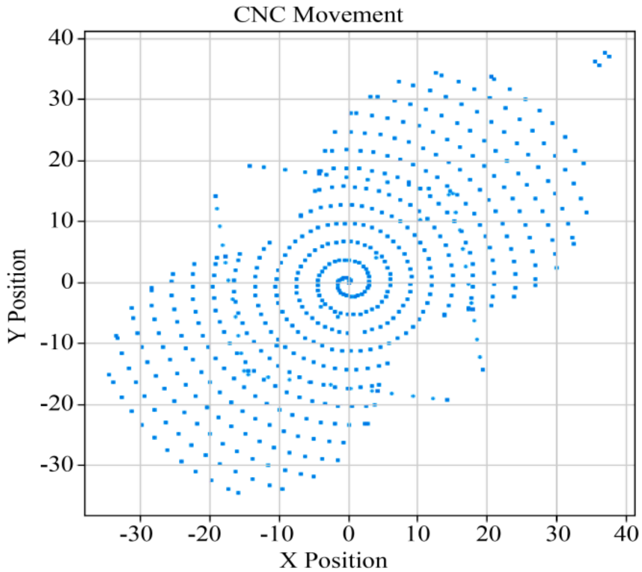


Fig. 11 CNC plot movement

Table 1. Machine learning algorithm evaluation

ML	Precision	Recall	F1-Score	Accuracy
LR	0.20	0.44	0.27	0.44
KNN	0.53	0.56	0.53	0.81
SVC	0.72	0.61	0.58	0.86
DT	0.78	0.77	0.78	0.80
RF	0.84	0.81	0.81	0.94
GB	0.92	0.89	0.90	0.96
AB	0.70	0.54	0.53	0.65

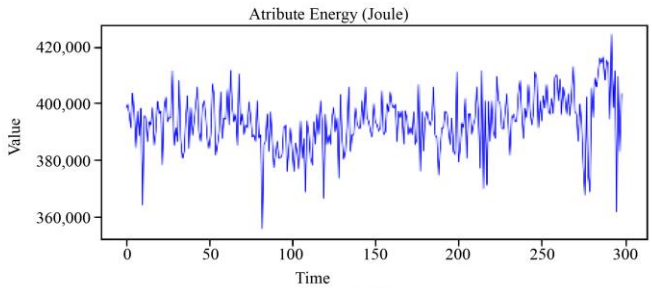


Fig. 12 Energy consumption graph

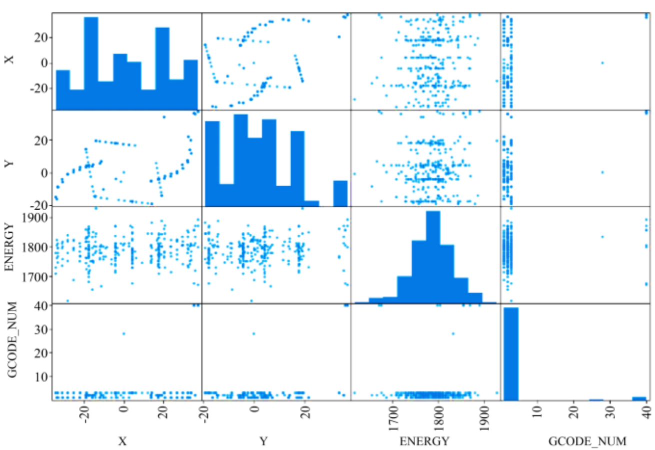


Fig. 13 CNC data distribution

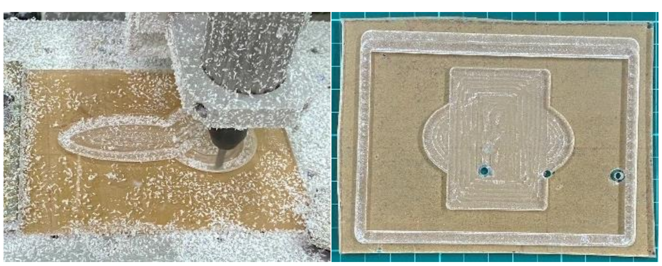


Fig. 14 Acrylic printing results

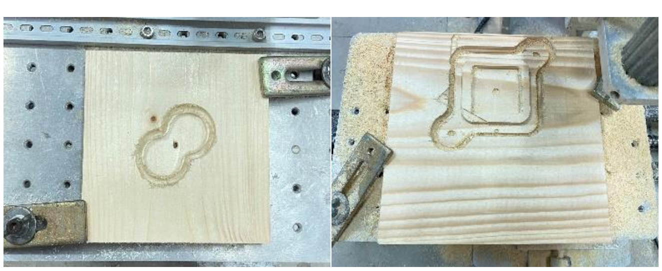


Fig. 15 Wooden printing results

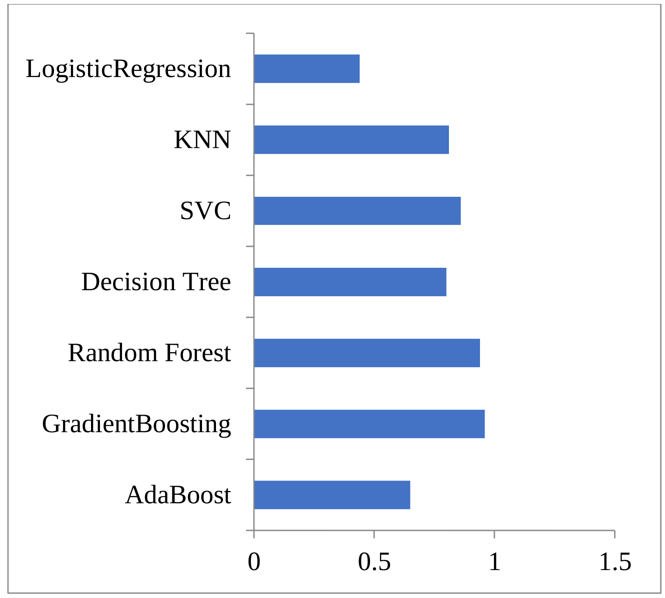


Fig. 16 Prediction accuracy

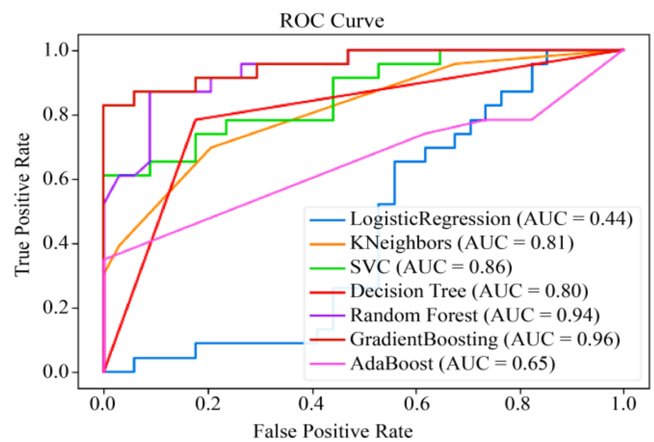


Fig. 17 ROC curve

4.4. Machine Learning Model and Evaluation

From the CAD model that has been made then printed using a CNC machine that has been assembled. The print of this machine is seen in Figure 14 with acrylic material, while in Figure 15, wood material is used. These four parts have been successfully printed with results and sizes that match the CAD design. During the printing process of these four parts, energy usage data is recorded.

Furthermore, the results of this recording are used as datasets to conduct training, testing and validation of several Machine Learning models. The calculation of Precision, Recall, F1-Score, and Accuracy values is an evaluation parameter in this study.

Table 1 presents the evaluation results of each model. The table shows the performance metrics of various Machine Learning (ML) models in forecasting the energy consumption trends of CNC machines. Expressed as the ratio of real positive predictions to all positive predictions provided by the model, precision shows how well the model reduces false positives. Recall highlights the model's capacity to catch all pertinent examples by calculating the ratio of real positive cases to true positive forecasts. The F1-Score presents the harmonic mean of precision and recall, offering a thorough evaluation of the model's performance. Accuracy is the proportion of accurate forecasts the model generates among all forecasts. The model with the lowest accuracy, recall, and F1-Score is the Logistic Regression (LR) model, indicating that it has a limited ability to classify instances effectively. Gradient Boosting (GB), on the other hand, exhibits the best precision, recall, and F1-Score, indicating its exceptional ability to accurately anticipate patterns of energy usage.

Overall, the Random Forest (RF) model achieves the highest accuracy among the models, while Logistic Regression (LR) and AdaBoost (AB) models show relatively lower performance across all metrics. These findings provide valuable insights into the effectiveness of different ML models in predicting energy consumption in CNC operations, aiding in the selection of appropriate models for optimizing energy efficiency. To be clearer, the accuracy data is presented in graphic form in Figures 16 and 17. It can be seen that Gradient Boosting occupies the highest accuracy and is then followed by Decision Tree and Random Forest.

The results of testing Machine Learning Classification models provide important information on how well these models work to predict patterns of energy usage in small CNC machines. Among the evaluated Machine Learning Classification models, Logistic Regression exhibited the lowest accuracy of 0.44, indicating its relatively weak performance in correctly classifying instances based on energy consumption patterns compared to other models. K-Nearest Neighbors (KNN) showed a modest accuracy of 0.56, surpassing Logistic Regression but trailing behind more sophisticated models like Decision Trees and Random Forests. Support Vector Classifier (SVC) displayed improved accuracy at 0.61, suggesting its effectiveness in capturing underlying patterns in energy consumption data.

Decision Tree Classifier showcased a significant accuracy improvement at 0.75, indicating its proficiency in capturing complex relationships between input features and energy consumption. Random Forest Classifier further enhanced accuracy to 0.81, demonstrating the effectiveness of ensemble methods in improving predictive performance. Gradient Boosting Classifier emerged as one of the top-performing models with an accuracy of 0.89, surpassing both Decision Trees and Random Forests due to its iterative approach in building an ensemble of weak learners.

However, the AdaBoost Classifier exhibited a lower accuracy of 0.54 compared to other models, suggesting its relatively less effective performance in this specific context. Overall, the results suggest that the Gradient Boosting Classifier stands out as the most effective model for predicting energy consumption patterns in the mini CNC machine, with an impressive accuracy of 0.89. However, further analysis may be warranted to understand the specific strengths and weaknesses of each model and optimize their performance for practical applications.

5. Conclusion

In summary, this study has effectively illustrated how inexpensive mini CNC machines can be integrated with Internet of Things (IoT)-enabled energy monitoring and machine learning techniques for predicting energy consumption. This presents a workable solution to the issues of accessibility and affordability in small-scale manufacturing and CNC education. This research has developed a small CNC machine based on the ESP8266 platform with meticulous attention to mechanical, electrical, and software design. This allows for extensive data collection and analysis of patterns in energy use during machining operations. Using a variety of machine learning classification techniques, including AdaBoost, Gradient Boosting, Random Forest, Decision Trees, K-Nearest Neighbours, Support Vector Classifier, and Logistic Regression, it has been determined that Gradient Boosting is the most accurate and robust method for predicting energy consumption in mini CNC operations.

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