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Design and Evaluation of a High-Efficiency Smart IoT Device Incorporating Embedded Tiny Machine Learning for Monitoring Asset Activity

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ABSTRACT
This article suggests a proof-of-concept gadget with an energy-efficient architectural design that can track the use of handheld power tools and identify construction-related activities (like various drilling jobs) as well as possible misuses (like drops). The device's design relies on RFID and WIFI module (ESP8266) communication. Wifi module is used for data exchange with a gateway, whereas RFID is used to identifyy the user. An accelerometer is included for tracking tool use, while sensors for temperature and humidity are used to keep an eye on storage conditions. Information processing at the edge is accomplished by using the Arudino uno that is included within the wifi module. In order to analyze the data directly on board and achieve low latency and great energy efficiency, a Tiny Machine Learning (TinyML) method is developed. The suggested gadget contains an incorporated TinyML algorithm that has been created to identify three distinct use classes: wood drilling, metal drilling, and no-load. The device was coupled to a construction rotary hammer drill to capture a dataset that included over 280 minutes of three-axis accelerations during various operations. This dataset was utilized to train and verify the algorithm.
Using a model size of around 30 kB, a neural architecture search was conducted to maximize the trade-off between accuracy and complexity, and an accuracy of 90.6% was obtained. Based on the testing findings, TinyML ran on the edge with an ultralow power usage of 550 nA in sleep mode and an 8 mA peak power consumption. With a basic 250-mAh coin battery, this leads to a balanced mix of low power consumption and edge processing capabilities, allowing the creation of a smart Internet of Things (IoT) device in the field with a long lifespan of up to four years in operation and 17 years in shelf mode. This study closes the gap between edge processing and fine-granularity data assessment by enabling extended battery lifetime operation of device degradation and utility analysis.

Keywords: Asset management, condition monitoring, construction 4.0, energy efficiency, low-power design, smart sensors, tool usage monitoring, wireless sensor networks

1. INTRODUCTION

The majority of the working chain in every construction business uses PPOWER equipment. Evaluating the use of power tools may significantly affect the sustainability of the industry. With the use of this data, maintenance interventions may be optimized, tool life cycles can be extended, and safety and productivity can all be raised.

Actually, improper usage or neglected maintenance may impede productivity and, in the worst situations,jeopardize human safety.

It significantly affects productivity in both situations and tangentially affects sustainability as a whole. Achieving a long operational life is one of the difficult problems involved in product design, and in order to do so, focused interventions and proper handling are required .

The benefits of digitization in sustaining a viable firm are becoming more widely recognized in the construction sector . Even yet, adoption is still hampered by a number of technological issues and cultural restrictions. Preserving the old process is crucial in light of the conservative industrial culture. Therefore, SmartTag has to be position-agnostic so that consumers may place it anywhere they think is most practical. Moreover, a lot of power tools are corded, which means that extra voltage conversion circuits are needed to provide the SmartTag. Aside from technological constraints, the largest obstacle to the seamless application of IoT as a true digitalization facilitator is the battery-operated gadget lifespan [11]. Technological advancements along with the current wave of IoT are opening up new possibilities for the design and development of powerful, intelligent, low-energy, compact, lightweight, and wireless sensor devices. wifi module (ESP8266), is one of the wireless technologies that enables energy-efficient meter-distance communication with a power budget of a few milliwatts.

New generations of Internet of Things (IoT) devices that are used for long-term monitoring of industrial equipment, tools, and other devices are made possible by the combination of wireless capabilities, sensors, and on-board signal processing.Because of the intricate and dynamic nature of how tools operate, evaluating their performance and predicting their lifespan and failure is becoming an increasingly critical topic to solve. Today's sensors are a precise technological instrument for gathering valuable data on the functionality, state, and operation of equipment and machinery. Particularly microelectro-mechanical systems (MEMS) inertial sensors, which are electronic instruments used in several monitoring applications to detect vibration, acceleration, and orientation using gyroscopes.

Monitoring the condition of a portable and reasonably compact gadget is becoming increasingly crucial as instruments get more intricate and costly. But, the current sensors aren't sophisticated enough on their own to glean meaningful information from the collected data. For further processing in the cloud, a node must stream the data collected by the existing sensors. This method raises security and privacy concerns in addition to increasing communication energy requirements and detection delay. Because of this, the majority of sensor systems in use today are designed to monitor medium- to large-sized stationary equipment or tools.

It is possible for an intelligent Internet of Things device to be produced and kept for an extended period of time before it is used, and its brief operational lifespan of a few weeks or months after activation may dissuade users from embracing these kinds of solutions.

The actual procedure might thus be split into two scenarios: one when the tool is used, and hence the gadget, is kept on a shelf, and another where the tool is used. Furthermore, the device's application scenario may involve a range of unpredictable work operations (such as drilling, hammering, chiseling, grinding, transportation, etc.), unintentional drops, and atmospheric conditions that subject the device to demanding and dynamic operating conditions similar to those found on construction sites.

As a result, many numbers had to be assessed for every scenario: While vibrations and consequent accelerations may be used for activity, operation, and drop identification, temperature and humidity can be monitored to track ambient conditions.

This paper specifically describes the architecture, implementation, and experimental assessment of a durable SmartTag with integrated sensors and edge intelligence for remote power tool monitoring.

The primary goal is to enable usage accounting and device deterioration by monitoring the use and conditions of industrial instruments. The Arudino uno, which is specifically designed for onboard information processing and data analytics with inertial sensors, powers the SmartTag. With the help of the improved CMSIS-DSP [27] libraries, this node can execute both conventional signal processing pipelines and cutting-edge machine learning (ML) and deep learning tasks. This study proposes and evaluates a neural network for activity detection and drilling material classification. The proposed model is trained and validated using a dataset of drilling accelerations against various materials spanning over 2700 s.

The core advancements of this article can be outlined as follows:

1. Codesigning the hardware and software of a novel smart IoT node that can record three-axis accelerations, temperature, and humidity in an ultralow-power manner.
2. collecting field data on accelerations from a prototype attached to a construction power tool duringdrilling, no-load, and transportation tasks.
3. searching the network architecture for an efficient and accurate tool activity recognition.
4. porting the designed ML model at the edge with extreme kernel size optimization to enable it to runon the battery-powered designed device.
5. analyzing the viability and performance evaluation on actual construction power tool data.
6. conducting an experimental evaluation of the device's functionality, power consumption, and batterylifetime.

2. RELATED WORK

A neural network technique similar to this has been presented in , whereby the authors categorize various rock kinds throughout the drilling process. Though in this study we show that drilling material categorization is doable with simply acceleration, the authors elaborate signals from five distinct physical parameters. Furthermore, as previously mentioned for , unlike SmartTag, which performs the acquisition and classification in a small, battery-operated device attached to the drill body, the sensors used in this system must be integrated into the drill body, and the signals are collected by external equipment. Furthermore, the model suggested in only makes use of dense layers, but our model makes use of convolutional layers to achieve equal accuracy with a highly optimized model size that can operate on devices with limited resources. A number of techniques are suggested to extract the activity carried out after data from three-axis accelerometers, gyroscopes, and magnetometers are collected and examined using an angle grinder and a cordless screwdriver. In contrast to activity recognition, our study concentrates on the material, enabling tool degradation accounting, and attains a comparable level of accuracy using a deep learning model that just needs accelerometer data. This leads to a considerable reduction in power consumption and system complexity.

The information obtained by the sensor node is expanded upon at the edge in our study. An very effective signal processing pipeline using a neural network is suggested. An effective neural network may be used to categorize the drilling material if the tool is presently being used, accelerometer data is used to detect tool use. Previous research has shown that accelerometers are a suitable match for assessing the health of devices . Additionally, the signal processing methods outlined above have been shown to extract valuable information from accelerometer data when employed in isolation. , while and used a convolutional neural network (CNN) to identify bolt-nut alignment. Our approach makes use of deep learning techniques to maximize the suggested solution's energy efficiency.

The idea has been used in SmartTag as well, as RFID is used for wake-up. For use-case situations such as the SmartTag, wake-up radios are a viable solution: a short-range wireless activation method has been selected to circumvent the lack of physical buttons on the finished goods. Reliability and sustainability of the sensor node are enhanced when no mechanical elements are exposed, particularly in the tough and dusty settings where SmartTags are supposed to function.

The productivity of employees has also been evaluated using motion tracking. Specifically, in an industry 4.0 context, examines productivity assessment techniques for the construction sector. There has been a push toward deep activity recognition with the current developments in deep learning. Most notably in the area of human activity recognition (HAR) , which uses accelerometer and gyroscopic data from smartwatches and smartphones to categorize human activity. Large and complex neural networks are used in the state-of-the-art deep learning technique to handle the data from wearable devices .

Even long short-term memory (LSTM) neural networks are used in the most complicated situations. The SmartTag application case for HAR is somewhat similar in that it involves classifying drilling tool activities for deterioration and usage accounting. The neural network's deployment device's computational capability, however, is where the main distinction resides. However, our study demonstrates that a feed-forward nonrecurrent CNN may be practical on a highly power- and computationally-constrained device and produce excellent performance in basic activity identification applications like tool monitoring, providing advantages of machine learning at the edge.

Despite being relatively new, small machine learning, or TinyML, has received a lot of attention in the literature. While inference may be calculated on the edge, even on devices with very limited resources, neural networks are typically trained on dedicated servers . Continuous learning approaches have been introduced recently , often using specially created structures . TinyML systems are becoming more and more popular, and in order to facilitate this growth, tools for benchmarking , and have been created to evaluate ML performances at the edge. Efficiency and sustainability were important considerations in the work and served as guiding principles in the creation of the SmartTag. The writers examine many articles within the Internet of Things domain, specifically focusing on Smart Cities. The sustainability of IoT nodes itself has become a significant concern and has been taken into consideration while creating the SmartTag.

In summary, this paper offers a fresh approach to utilization analysis and asset monitoring. An effective neural network that solely makes use of accelerometer data has been developed for the purpose of classifying drilling materials, allowing for the analysis of tool degradation and utilization. It has also been successfully implemented on a device with limited resources to enable edge inference, balancing accuracy against model size and inference energy. Additionally, a new ultralow-power sensor node that runs on a tiny coin cell battery for over four years in operation and seventeen years in storage has been unveiled.

3. PROPOSED SYSTEM AND IT'S ARCHITECTURE

The ultralow power consumption and energy efficiency of the suggested sensor node were incorporated into its architecture. Fig. 1 shows a schematic illustration of the suggested solution.

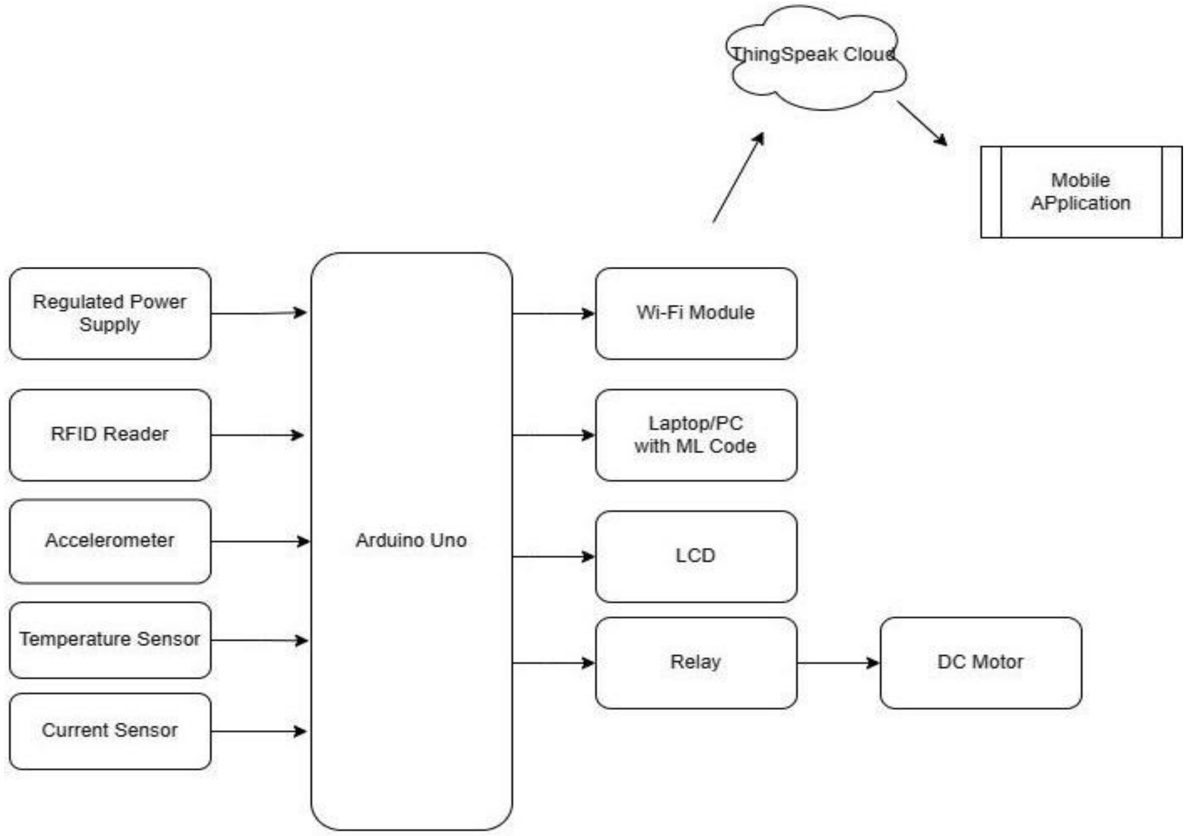

Fig.1. schematic illustration of proposed system

- **System Components**

Arudino uno have good processing power, with a core speed of up to 20 MHz and wifi module(ESP8266) with a speed up to 160MHz. There are numerous different microcontrollers and microcontroller platforms accessible for physical computing. Parallax Basic Stamp, Netmedia's BX-24, Phidgets, MIT's Handyboard, and numerous others offer comparative usefulness. These apparatuses take the chaotic subtle elements of microcontroller programming and wrap it up in a simple to-utilize bundle. Arduino additionally rearranges the methodology of working with microcontrollers; moreover it offers some advantages for instructors, students, and intrigued individuals.The RC522 is a RF Module that consists of a RFID reader, RFID card and a key chain. The module operates 13.56MHz which is industrial (ISM) band and hence can be used without any license problem. The module operates at 3.3V typically and hence commonly used in 3.3V designs. It is normally used in application where certain person/object has to be identified with a unique ID.

Next, two I2C-enabled sensors were selected: one for measuring temperature and humidity and the other for measuring acceleration, which is the most crucial sensor for assessing how well tools and equipment are being used. Sensirion's SHTC3 is the predecessor, with a usual accuracy of ±2% for relative humidity and ±0.2 ◦C for temperature. It shares compatibility with our node's low-voltage rail, which is set at 1.8 V to maximize power consumption. The sensor has been power gated in order to further minimize power usage while not in use. . It has four separate acceleration measurement scales, ranging from 2G to 16G, with a noise density as low as 90 µG/√Hz in the 2G range and a sensitivity of ±3% mG/digit on all scales. With a current consumption of only a few µA for measurements obtained in low-power mode and 50 nA in the lowest power mode, the power numbers are equally outstanding. We take use of an RFID chip to awaken the MCU from deep slumber and switch it from shelf mode to working mode, since physical buttons are not believed to be included in the final design. When an RFID is present, toggles a pin to collect the necessary energy and communicate data.

- **Proposed System Description**

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Python Machine Learning Script: The system utilizes a Python machine learning script to analyze usage data collected from sensors and predict maintenance needs. By analyzing usage patterns and historical data, the script can identify potential issues and recommend proactive maintenance actions to minimize downtime and prevent equipment failures.

Mobile Application Interface: The system can be accessed and monitored through a dedicated mobile application interface, allowing users, supervisors, and maintenance teams to view real-time data, receive alerts, and coordinate maintenance activities.

Overall, the proposed Smart Tool Usage Monitoring System offers a comprehensive solution for efficient, safe, and accountable tool management in professional and industrial settings. By leveraging RFID technology, sensor integration, predictive maintenance capabilities, and seamless communication, the system aims to optimize tool utilization, reduce downtime, and enhance operational efficiency.

4. EDGE ML

Among the many advantages of edge computing is its ability to reduce latency, making it possible to run applications with stringent time constraints. Reducing the amount of bandwidth required and on-air collisions significantly involves transmitting just the significant characteristics that were derived from the data. Furthermore, a sensor node's wireless communication uses the majority of its power, therefore restricting data would inevitably shorten the node's battery life. Data security and privacy also clearly benefit from this approach, as only processed data is transferred and raw data never leaves the sensor node, making listening in on private conversations impossible.

While there are numerous applications where TinyML at the edge might be useful, for the sake of this study, we established a specific but very pertinent use-case to test the capabilities of the suggested SmartTag. To specifically recognize and differentiate between the following working situations, a three class machine learning method was created and developed.

1. No-Load: There is no load imposed while the tool is operating.
2. Metal Drilling: Drilling equipment for metal.
3. Wood Drilling: Wood drilling equipment.

When it comes to the tool's use, the aforementioned classes together enable a more detailed resolution. Battery and wireless bandwidth are conserved by the very effective data compression provided by the TinyML algorithm operating at the edge. The edge ML estimates may then be further processed in the cloud using more sophisticated ML algorithms to acquire further insights to enhance maintenance, productivity, and overall sustainability of businesses like the construction industry. This process can be combined with the temperature and humidity readings.

- **Data Collection and Analysis**

To train and evaluate the machine learning technique, an infield accelerometer drilling activity dataset was obtained. A professional drilling tool (Hilti TE 30-A36) with a SmartTag affixed yielded the following kind of data.

1. No-Load: Using a 10 mm × 170 mm drill bit, the tool was operating without any load and without coming into contact with any material. Both the drilling and hammering modes have been included inthe no-load data capture in order to have a more representative dataset.
2. Metal: A 10 mm × 90 mm drill bit was utilized to drill a hole into steel material using the tool. Since this kind of material doesn't need a pounding function, the tool was set to drill mode.
3. Wood: A 10 mm × 90 mm drill bit was used to drill a hole into the wooden substance. Since this kind of material doesn't need a hammering function, the tool was set to the drilling mode.

Using an 800 Hz sample frequency, the accelerometer signal was obtained from the SmartTag. Raw accelerometer data for a total of 45 minutes, or 3.04 GB, has been gathered.

The gathered accelerometer data during drilling activity is shown in Fig. 2, which takes into account a window of 448 samples at all times. Data analysis of the utilization scenarios under investigation using infield drilling tests. Conversely, the non-negligible variation of the Wood, Metal, and No-load signals is instantly apparent. The signals would substantially overlap if the three aforementioned classes were placed on top of one another. Additionally, it is evident that the Wood and Metal signals exhibit significant variation at frequencies where the means seem to be different from one another. Conversely, No-load has a distinct peak with little fluctuation at around 225 Hz. Therefore, it stands to reason that No-load will be easier to differentiate from Wood and Metal—while still being non-trivial.

This intricate categorization job is being handled by a neural network. The difficult job of distinguishing between the three problematic classes—Wood, Metal, and No-load—will be handled by a neural network.The system is anticipated to be unavailable.

The majority of the time, the system is anticipated to be in a nonworking condition (i.e., no drilling activity). When the system reaches a drilling state, which happens seldom, the more computationally demanding neural network operation will be executed.

Fig.2. Accelerometer data during drilling activity

5. RESULTS AND IT'S ANALYSIS

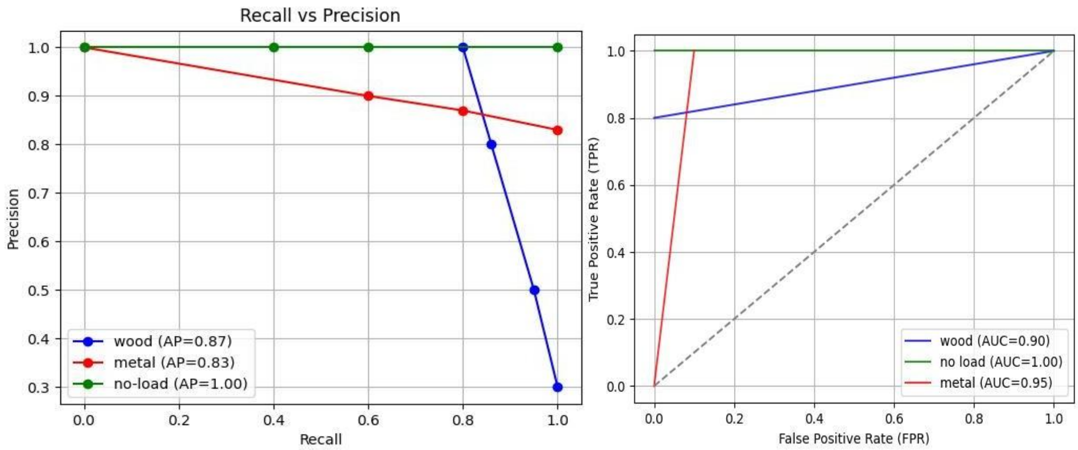

Fig.3. Left: Precision recall plot of the full precision neural network. Right: whole precision neural network's ROC plot

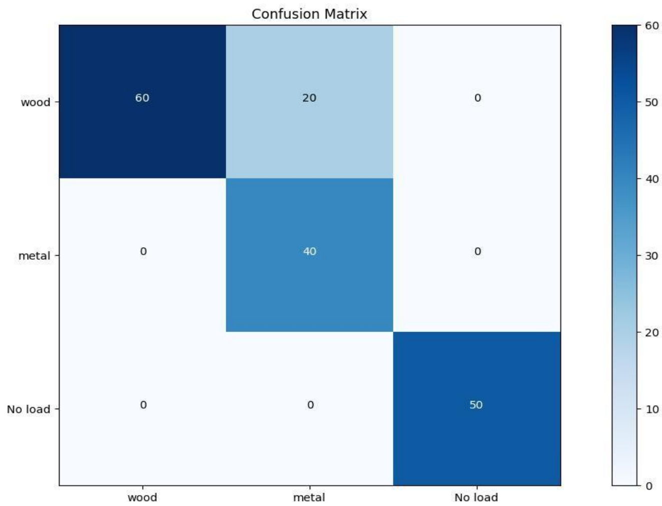

Fig.4.Confusion matrix of the full precision neural network

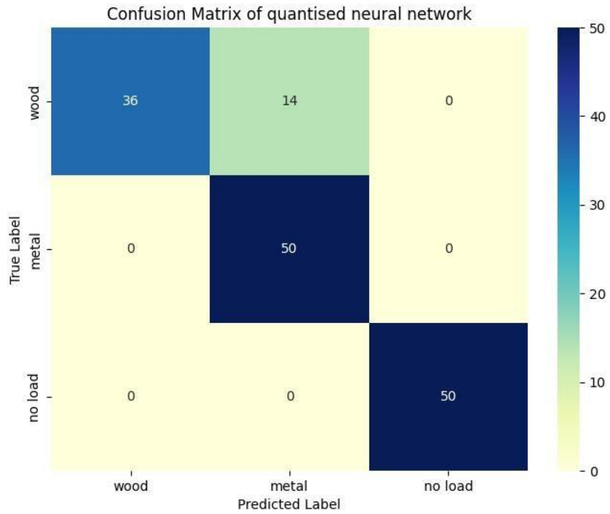

Fig.5. Confusion matrix of the quantized neural network.

A held out balanced test set consisting of 150 accelerometer data windows with 448 samples each was used to assess the resulting neural network architecture. The model's classification performance metrics for the three classes of interest are shown in Fig. 3. Overlaying the F1-score isobars, each class's accuracy and recall are assessed in a One vs. All manner on the left side of Figure 3. The One vs. All receiver operating characteristic (ROC) plot, with the dashed diagonal signifying the no-skill threshold, is shown on the right side of Figure 3.

It is significant to note that while each class's test set is balanced, there is a 1:2 imbalance in the One vs. All assessment. Therefore, the important metrics to pay attention to are accuracy and recall, with ROC being included for completeness.

Lastly, to provide an objective and thorough model assessment, Fig. 4 displays the confusion matrix of the test set evaluation. It is evident from looking at Fig. 4that, out of the three groups of interest, Metal and Wood seem to be the hardest to differentiate the premise of Section IV-A—that Wood and Metal are more difficult to identify from one another than No-load—is confirmed. In summary, the suggested design seems to be well suited for the drilling activity categorization assignment in Wood, Metal, or No-load. With a 93.3% accuracy rate on the balanced test set, it enables a more in-depth examination of the use and deterioration of the drilling tool by integrating the neural network on the SmartTag.

- **Power consumption**

To evaluate power consumption and proper performance, the SmartTag has been tested in both shelf and operational modes. the present consumption of both systems in shelf mode, in which the node waits for RFID to wake it up and all of the components power off. The humidity and temperature sensor has been power gated since its power usage in low-power mode is equivalent to that of the MCU, which consumes the bulk of power. Plotting the power profile of the Wifi module(ESP8266)-based sensor node as it performs the standard workload of sensor collection and data transmission from sensors to the cloud is shown in Fig.6.

The accelerometer provides a total of 1024 samples at a sampling rate of 800 Hz. A moving average is given in red, while the raw data are tinted blue.

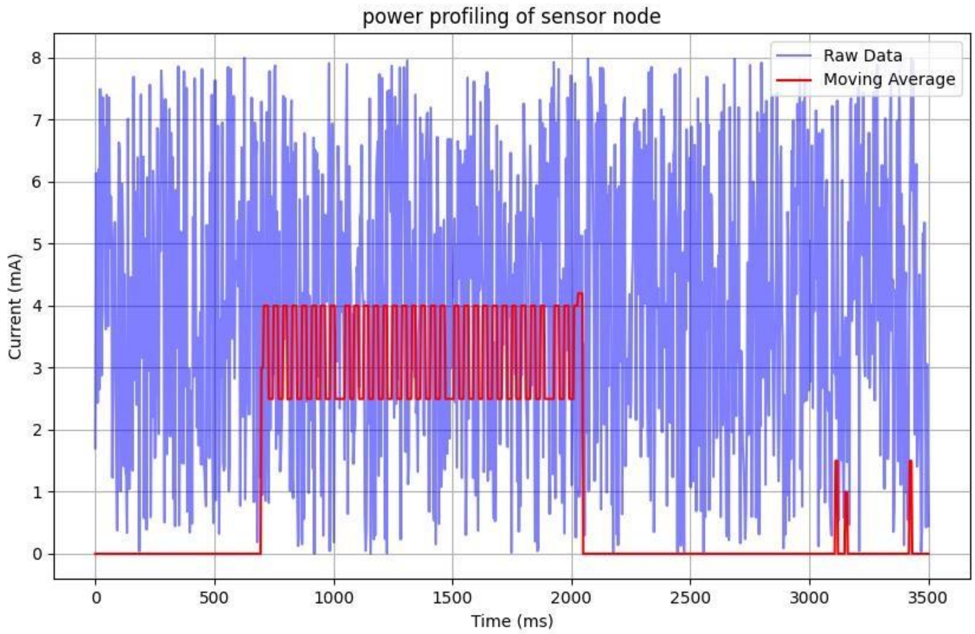

Fig.5.. Power profiling of the sensor node during sensor reading and sensor data transmission

6. CONCLUSION

The purpose of this study is to allow condition and use monitoring of mobile power tools and machines in construction sectors by designing, implementing, and evaluating an ultralow-power IoT wireless sensor node. In order to evaluate the gadget, real-world data was gathered while it was connected to a drill tool used in construction. This article demonstrates how a smart node with a 250 mAh coin battery may last for over four years while monitoring accelerations, storing ambient conditions, and using neural network models to do inference at the edge. The ported TinyML neural network demonstrates that power tool activities, including various drilling operations, can be accurately categorized with a 90.6% accuracy using a tiny wireless node connected to the tool. The work's outcomes allow for more precise utility monitoring of power tools, on-the-spot information processing, and extended battery life preservation. Aggressive power management enabled the node to spend just 3 μW while in sleep mode and only wake up the system when absolutely essential, resulting in such outcomes. In order to enhance the precision of the deterioration and utility accounting of the power tool under investigation, it might be beneficial to distinguish between other classifications, such as concrete drilling and chiseling. In order to achieve a proof of concept, the analysis conducted in this study was restricted to the three classes shown in Fig. 2. The data was gathered by attaching the SmartTag consistently to the same spot on the tool.

Future research can therefore focus on improving the ML algorithm's generalization ability to various SmartTag attaching positions on the power tool and examine what data and working classes are required to estimate degradation and utility analysis of the tools as efficiently as possible.

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