Research Report

Sound-Based Machine State Monitoring using Artificial Intelligence: A Case Study for Additive Manufacturing Machine

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ME49800ZU: Smart Manufacturing

Fall 2024

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Abstract

In this study, inspired by *Operation and Productivity Monitoring from Sound Signal of Legacy Pipe Bending Machine via Convolutional Neural Network* [1], who utilized sound signals and convolutional neural networks (CNNs) to monitor pipe bending machines, we extend these findings to a modern manufacturing setup. Using a custom-designed sound sensor attached to a Renishaw AM-400 Additive Manufacturing machine, we collected audio data representing its *Printing* and *Off* states. The collected data was preprocessed to remove irrelevant noise, segmented into meaningful frames, and analyzed through feature extraction methods such as RMS, spectral centroid, spectral bandwidth, FFT energy, and frequency band energy.

A CNN model was developed to classify the two machine states, incorporating advanced techniques such as early stopping and dropout to prevent overfitting. The results were exceptional, achieving 100% accuracy in distinguishing between the *Printing* and *Off* states. This validates the potential of sound as a monitoring modality in modern industrial processes.

Furthermore, this study highlights that additional state labels, such as "Bending," "Cooling," or "Anomaly," could be incorporated into the framework with further feature extraction and model refinement. The long-term objective is to enable real-time sound-based monitoring systems for predictive maintenance and risk management in smart manufacturing environments. Such systems could seamlessly integrate into IIoT ecosystems, providing intelligent, autonomous, and adaptive monitoring solutions for diverse industrial settings.

1 Introduction

Recent advancements in smart manufacturing, prognostics and health management (PHM), and Industrial Internet of Things (IIoT) frameworks have significantly reshaped the landscape of industrial operations, thriving in the era of the Fourth Industrial Revolution. These developments emphasize real-time monitoring, predictive maintenance, and automation, thereby minimizing risks and optimizing productivity. In this context, monitoring the operational states of machines is a crucial component for detecting anomalies, ensuring timely interventions, and mitigating risks. Traditional methods for machine monitoring, such as visual data (e.g., cameras) and software-based alerts, have been widely used but often face limitations due to high costs, complexity, and intrusive installation requirements. Sound, as a non-intrusive, simple, and cost-effective alternative, has gained attention as a viable solution for monitoring. Unlike visual systems, sound data can be captured using affordable and simple installations, and its non-invasive nature makes it particularly attractive for industrial settings. However, challenges such as noise interference and uncertainties have historically hindered the reliability of sound-based monitoring systems. Efforts to overcome these challenges and reduce the gap between legacy systems and modern IoT-compatible monitoring solutions have highlighted the potential of innovative sensing methods. For example, the *Method for Automatically Recognizing Various Operation Statuses of Legacy Machines* [4] introduced a novel approach for accurately monitoring operational statuses in legacy manufacturing equipment using unsupervised learning and clustering techniques. This method addressed issues such as tool changes and process variability, demonstrating that operational statuses could be reliably recognized with minimal intervention, even in complex and dynamic manufacturing environments. By effectively adapting older systems to modern monitoring frameworks, this study provides valuable insights for overcoming barriers in sound-based monitoring systems, reinforcing the importance of advanced methods for industrial applications. Recent research has also demonstrated that deep-learning techniques can further enhance the applicability of sound-based monitoring. For instance, *Scalogram-Based CNN Approach for Audio Classification in Construction Sites* [3] and *Advanced Sound Classifiers and Performance Analyses for Accurate Audio-Based Construction Project Monitoring* [5] established the practical efficacy of sound sensing in construction environments. These studies demonstrated that CNN-based models could accurately classify audio data from complex construction sites, where visual or traditional monitoring methods might fail due to environmental constraints. By proving the reliability of sound-based monitoring in challenging real-world conditions, these works not only validate the feasibility of such systems but also provide critical motivation for the broader applicability of sound sensing across industries. This connection reinforces the value of our research, which builds on the foundational insights of these studies to explore sound-based monitoring in industrial machine settings.

Building upon these advancements, this study focuses on validating the use of sound data for monitoring the operational states of machines in an industrial context. Specifically, we aim to mimic the expertise of professionals who can detect machine anomalies through auditory observation. This study investigates the distinction between two operational states—*Printing* and *off*—of a Renishaw AM-400 Additive Manufacturing machine. To achieve this, one-hour raw audio data for each state was collected, and meaningful features such as RMS, spectral centroid, spectral bandwidth, FFT energy, and frequency band energy were extracted. A Convolutional Neural Network (CNN) model was then trained to classify these states based on the audio data. To ensure robust performance and prevent overfitting, techniques such as early stopping and dropout were implemented during the training process. By leveraging these advanced techniques and addressing the challenges of sound-based monitoring, this research contributes to the broader goal of enhancing industrial safety and efficiency through intelligent systems. Our findings demonstrate that sound can serve as a reliable, cost-effective, and non-invasive alternative for machine monitoring, offering a practical solution for modern industrial operations.

2 Method

Monitored Machine for the study is an additive manufacturing machine that employs powder bed fusion. Additive manufacturing is a manufacturing process that stands in contrast to subtractive-manufacturing methods. Specifically, Powder bed fusion (PBF) is a cutting-edge additive manufacturing technology that utilizes a high-powered laser to selectively melt fine metal powders in a layer-by-layer process, enabling the creation of intricate geometries with exceptional precision [6]. During the printing process, the laser rapidly scans the metal powder bed, generating localized melting and solidification. This produces characteristic sounds, including sharp, high-frequency tones from the laser-melting interaction and lower-frequency noises from the powder recoating mechanism. These acoustic signatures are critical for understanding the operational states of the machine. In this study, a Renishaw AM400 machine, which employs powder bed fusion technology, was used to collect raw audio data. Specifically, the machine's *Printing* and *Off* states were monitored to serve as the primary dataset for this analysis.

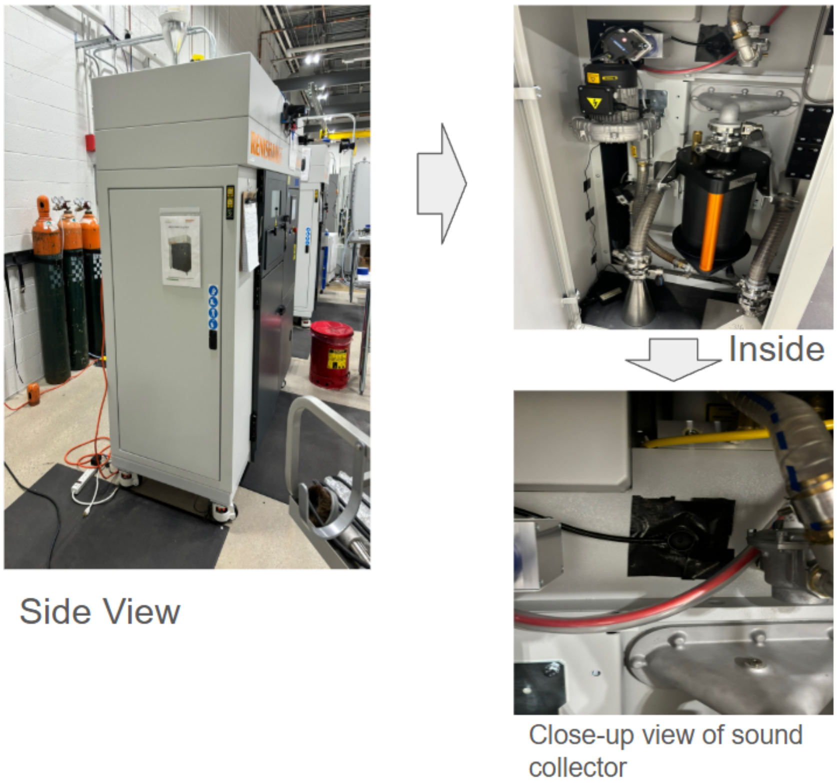

Figure 1. Sound Sensor Deployment

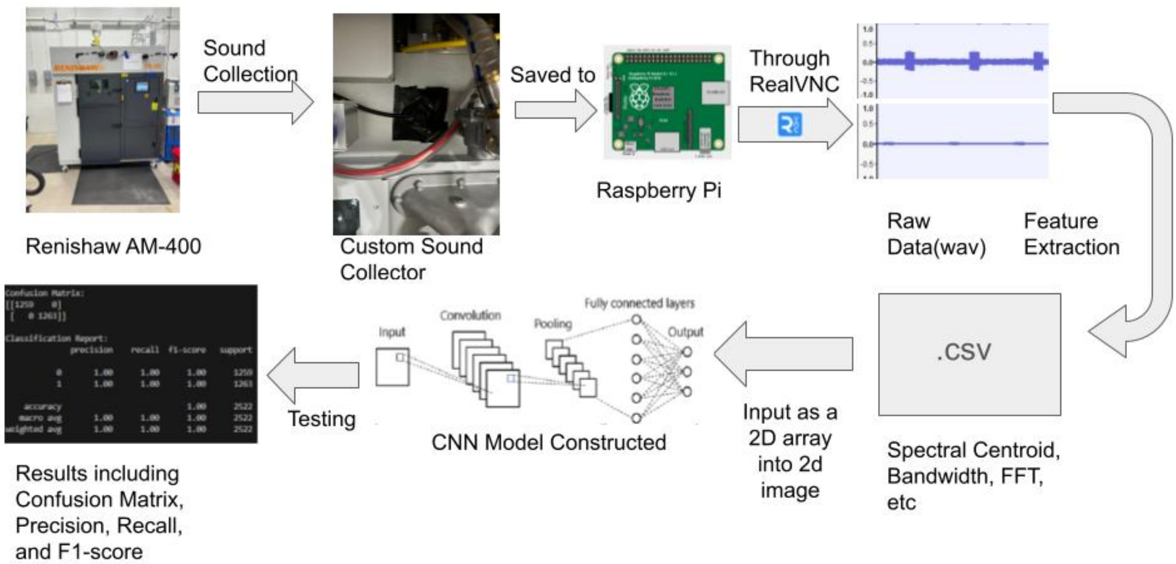

Figure 2. Method Outline

2.1 Data Collection

To collect high-quality audio data for this study, a custom-made sound sensor was developed and strategically deployed on the Renishaw AM400 machine. The sensor was crafted using a modified stethoscope, with its tubing cut just before the U-shaped split leading to the earpieces. This modification allowed the tubing to be integrated into a 3D-printed frame designed to house the sensor securely. On the opposite end, the tubing was connected to a USB cable, enabling seamless integration with a Raspberry Pi. The Raspberry Pi functioned as an edge device, collecting raw audio data in real-time from the sound sensor and transmitting it with lossless integrity. This ensured the reliability and accuracy of the collected data, making it well-suited for preprocessing and subsequent machine learning applications. The placement of the custom sensor was carefully considered to balance effective sound capture and non-intrusiveness to the Additive Manufacturing process. Direct placement within the printing chamber was avoided to prevent interference with the printing operations and protect the sensor from potential damage due to high temperatures or moving components. Instead, the sensor was affixed to the internal side panel of the Renishaw AM400 machine, directly opposite the wall of the printing chamber. This placement allowed the sensor to capture sufficient sound data without disrupting the printing workflow. Figure 1 illustrate this setup. The sensor is deployed on the internal side panel, showing its stabilization with black tape and the buffering solution applied to the diaphragm of the stethoscope head. The buffering solution played a critical role in reducing sound roughness and enhancing audio quality, ensuring that the captured sound signals were clear and suitable for feature extraction and model training. By securing the sensor in this location, the study achieved a balance between non-intrusive placement and effective sound capture. The Raspberry Pi functioned as an edge device, collecting raw audio data from the sound sensor. The data was streamed in real-time with lossless integrity to ensure reliability, making it suitable for preprocessing and subsequent machine learning applications. The collected audio data included two operational states of the Renishaw AM400: the *Off* state and the *Printing* state. Each state was recorded continuously for one hour. To ensure that the collected data was representative and reliable, the sensor was calibrated to minimize environmental noise and optimize sound fidelity. These steps ensured that the audio data was of high quality, providing a robust foundation for the subsequent data preprocessing and analysis phases.

2.2 Dataset Preparation

Table 1. WAV File Details

Attribute	**Value**
Bitrate	768 kbps
Channels	1 (Mono)
Sampling Rate	48,000 Hz
Bit Depth	16 bits

To prepare the audio data for effective analysis and classification, a comprehensive preprocessing strategy was implemented. This process involved three key steps: noise cropping, data reduction, and segmentation, each designed to improve the quality and usability of the dataset. First, periodic compressor noises were identified in the recordings of both the *Printing* and *Off* states. Since these sounds were unrelated to distinguishing between the two states, they were removed to ensure that the model focused on features directly relevant to state classification. This step effectively reduced noise and enhanced the dataset's overall quality.

Next, the original 1-hour recordings for each state were reduced to 15-minute segments. This decision was informed by the observation that both machine states exhibited consistent patterns throughout the hour-long recordings. By selecting shorter segments, the dataset remained sufficiently diverse for training and testing while also allowing portions of the data to be reserved for future experiments or cross-validation. This reduction ensured efficient training and balanced representation of both states. Finally, the 15-minute audio recordings were segmented into 1-second frames with an 80% overlap between consecutive frames. This approach significantly increased the number of training and testing samples, providing a high temporal resolution for capturing transient features while preserving the continuity of audio patterns. These 1-second segments formed the foundation for extracting meaningful features and training the classification model. In this study, audio data from each 1-second segment was analyzed to extract a set of key features critical for distinguishing machine states. These features and their mathematical representations are detailed below, along with an explanation of their significance. The Root Mean Square (RMS) measures the average energy of the signal, defined as:

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

where x_i represents the individual audio samples, and N is the total number of samples. This feature is crucial for assessing the overall loudness or power of the signal, which often correlates with machine activity levels. The Spectral Centroid indicates the "center of mass" of the frequency spectrum, given by:

$$\text{Spectral Centroid} = \frac{\sum_f f \cdot S(f)}{\sum_f S(f)}$$

where $S(f)$ is the magnitude of the spectrum at frequency f. This feature helps characterize the brightness or sharpness of the sound, which can vary with different machine states. This feature is added for further improvement and possibility of other labels in future study. The Spectral Bandwidth describes the width of the frequency spectrum, calculated as:

$$\text{Spectral Bandwidth} = \sqrt{\frac{\sum_f (f - \text{Spectral Centroid})^2 \cdot S(f)}{\sum_f S(f)}}$$

It measures the spread of frequencies around the spectral centroid, capturing variations in timbre or texture of the sound. This is used because machines in operation often exhibit distinct bandwidth characteristics due to specific mechanical vibrations and noises. The FFT Energy is the total energy in the frequency domain, defined as:

$$\text{FFT Energy} = \sum_f |X(f)|^2$$

where $X(f)$ represents the Fourier-transformed signal. This feature captures the overall energy distribution in the frequency domain, useful for distinguishing machine operations. The FFT Peak Frequency identifies the dominant frequency within the segment:

$$\text{FFT Peak Frequency} = \arg\max_{f} |X(f)|$$

This feature pinpoints the frequency with the highest amplitude, which can be directly linked to specific machine behaviors or vibrations. The Frequency Band Energies partition the frequency spectrum into specific ranges and compute the energy within each band. These are defined as:

$$\text{Low Band Energy (0-1000 \quad Hz)} = \sum_{f=0}^{1000} |X(f)|^2$$

$$\text{Mid Band Energy (1000-3000 \quad Hz)} = \sum_{f=1000}^{3000} |X(f)|^2$$

$$\text{High Band Energy (3000-6000 \quad Hz)} = \sum_{f=3000}^{6000} |X(f)|^2$$

$$\text{Very High Band Energy (6000+ \quad Hz)} = \sum_{f=6000}^{\infty} |X(f)|^2$$

These features capture the distribution of energy across various frequency ranges, helping to identify patterns associated with machine activity, noise, or vibrations. The Total Energy is the cumulative energy across all frequency bands:

$$\text{Total Energy} = \sum_{f} |X(f)|^2$$

This feature is another measure of overall signal power, providing a holistic view of energy distribution. Finally, the High Energy Pattern is a binary feature indicating whether the segment's RMS exceeds a predefined threshold. For this study, threshold is set to 0.02 since all segment for *printing* exceeds 0.02 whereas *Off* does not. Formula is given as:

$$\text{High Energy Pattern} = \begin{cases} 1 & \text{if RMS} > T \\ 0 & \text{otherwise} \end{cases}$$

This feature helps quickly identify segments with significant energy levels, often linked to active machine states. These extracted features collectively enable robust classification of machine states by capturing both time-domain and frequency-domain characteristics of the audio signal. The reason behind extracting a total of 11 features is to open the possibility for other states to be labeled and incorporated into the system. The extracted features from both the *Printing* and *Off* states were combined into a single dataset, with a label indicating the state of the machine (**1** for *Printing*, **0** for *Off*) indicated in Table 2. This dataset was used to train the machine learning model, ensuring a balanced representation of both states.

Table 2. State Label.

Label	Definition
Off,0	The machine is powered off, with no active operations.
Printing,1	The machine is actively in operation, with the laser sintering material to produce the product.

3 Convolutional Neural Network (CNN) Modeling

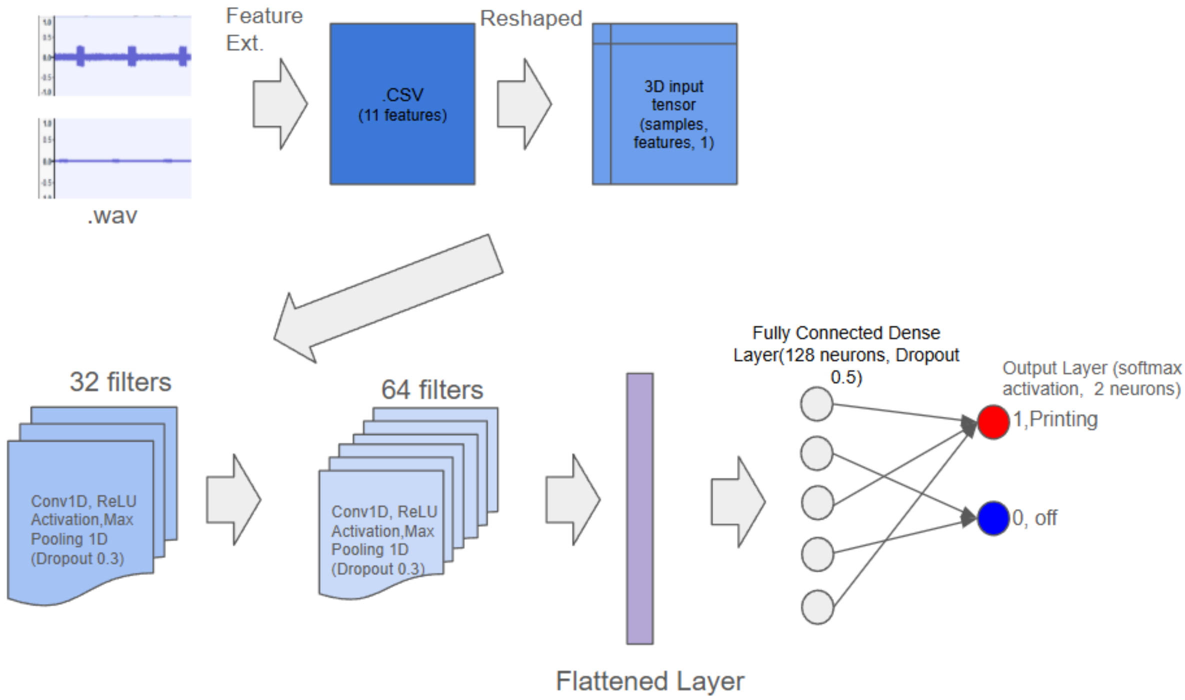

Figure 3. CNN Modelling Outline

Convolutional Neural Networks (CNNs) are a type of deep learning model designed to process data with a grid-like topology, such as images or structured signals. CNNs are particularly well-suited for tasks involving spatial hierarchies, enabling them to automatically learn meaningful patterns from raw data through a layered structure of convolution, pooling, and fully connected layers [2, 7]. In a typical CNN workflow, the input data first passes through convolutional layers, where filters (kernels) slide over the data to extract features such as edges, shapes, or textures. These extracted features are then downsampled through pooling layers, which reduce the data's dimensionality while retaining its most important aspects. Finally, the flattened feature maps are fed into fully connected layers, where the network combines learned features to make predictions. Activation functions, such as ReLU, introduce non-linearity to the model, enabling it to capture complex relationships within the data [2, 7].

This study utilizes a CNN to classify the operational states of a Renishaw AM400 Additive Manufacturing machine based on sound data. The choice of CNN is particularly appropriate for this application because of its capability to learn sound patterns from features like RMS, spectral centroid, and FFT energy while remaining computationally efficient. Therefore, suitable for this research. For the Particular CNN model constructed for this research, CNN model architecture consisted of several key components. The input layer accepted a 3D tensor representing the extracted features (11 features) for each segment. these dimension includes samples, features, and 1 channel since it is sound data. If it was an image, we would have used 3 channels (R, G, B). The model included two convolutional layers: the first applied 32 filters with a kernel size of 2, followed by ReLU activation, batch normalization, and max pooling. The second convolutional layer used 64 filters with a kernel size of 2, also followed by ReLU activation, batch normalization, and max pooling. Dropout layers were incorporated after each convolutional layer to prevent overfitting, with dropout rates of 30% for the convolutional layers and 50% for the dense layers. A fully connected dense layer with 128 neurons and ReLU activation was included to capture high-level feature representations, while the output layer consisted of 2 neurons with a softmax activation function to classify the two output classes: *Printing* and *Off*. The model was compiled using the Adam optimizer, categorical cross-entropy as the loss function, and accuracy as the evaluation metric.

4 Results and Discussions

To evaluate the robustness of the Convolutional Neural Network (CNN) model, audio files representing the *Printing* and *Off* states of the Renishaw AM400 machine were used for testing. Similar to the training data, the test files were cropped to remove compressor noise. While the training dataset was prepared from the first 15 minutes of the 1-hour recordings, the test data was extracted from a randomly selected 10-minute interval later in the recordings that did not overlap with the training segments. The same features—such as RMS, spectral centroid, spectral bandwidth, FFT energy, frequency band energies, and high energy patterns—were extracted from these test files, ensuring consistency in the preprocessing pipeline. The Convolutional Neural Network (CNN) was trained using a processed dataset, with the ratio of 70:30 with data allocated for training and validation. The model was trained for up to 100 epochs with a batch size of 32, and early stopping was employed to prevent overfitting. During the training process, the results were outstanding.

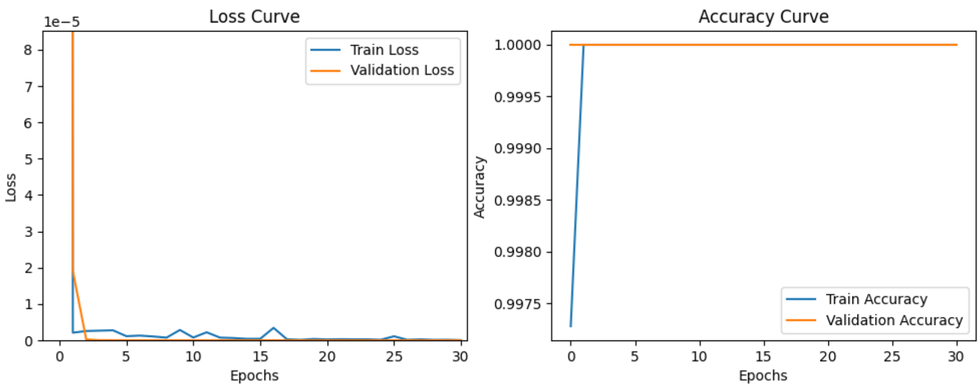

Figure 4. Loss and Accuracy Curves of CNN Training. The figure shows rapid loss reduction and stable, high accuracy across epochs.

By the second epoch, the training accuracy had already reached 100%, and the validation accuracy also achieved 100%, highlighting the model's excellent generalization capability. The loss for both training and validation decreased significantly throughout the epochs, with the validation loss approaching near-zero values. This indicates that the model converged effectively. To address potential overfitting, early stopping was triggered for most cases, after 10 to 30 epochs when no further improvements in validation loss were observed. This ensured that the training process remained efficient and the model did not overfit the training data. Further evaluation of the model's performance was conducted using the confusion matrix and classification report for the validation set. Below is the overview of the evaluation metrics used in this study. Precision measures the proportion of correctly identified positive cases (e.g., *Printing* state) out of all predicted positive cases. A high precision indicates that the model minimizes false positives. The formula for precision is:

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

Recall, also known as sensitivity, evaluates the proportion of actual positive cases correctly identified by the model. A high recall value ensures that the model rarely misses positive cases. The formula for the recall is:

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

The F1-Score is the harmonic mean of precision and recall, balancing both metrics effectively. It is particularly useful in scenarios where the dataset may be imbalanced, as it considers both false positives and false negatives. The formula for the F1-Score is:

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

These metrics revealed perfect classification for both classes, *Printing* and *Off*. Precision, recall, and F1-scores were all recorded at 1.00, confirming that the features extracted during preprocessing and the model's architecture were highly effective in distinguishing between the two machine states.

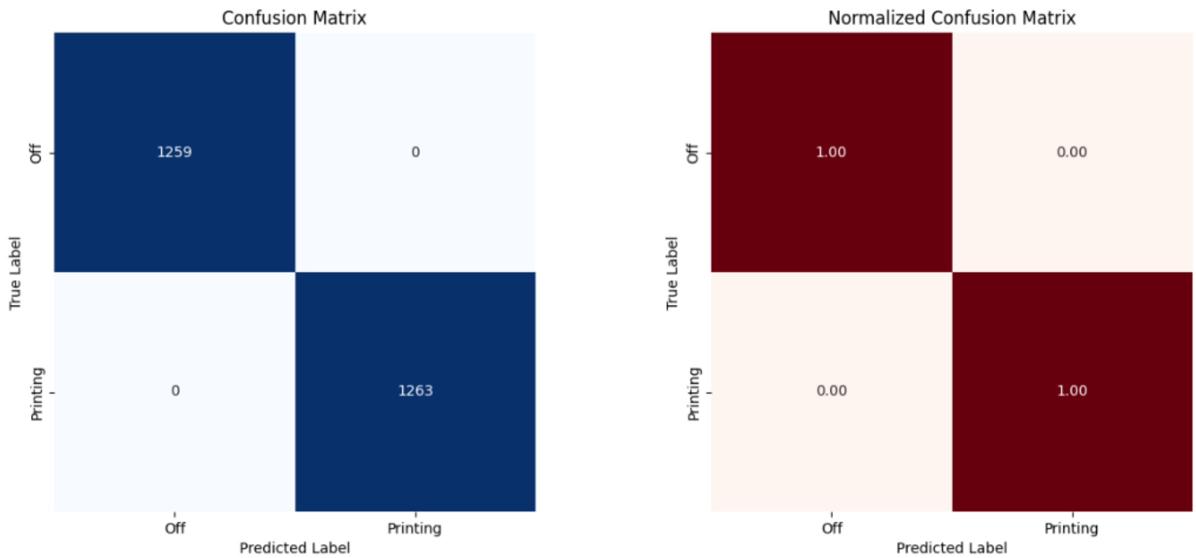

Figure 5. Confusion Matrix for CNN Model Training

To evaluate the robustness of the trained CNN model, separate audio files representing the *Printing* and *Off* states of the Renishaw AM400 machine were tested. The test data was carefully prepared to ensure independence from the training set by selecting a random 10-minute interval from each state, with no overlap with the training data. Compressor noise was cropped, and the audio files were segmented into 1-second frames with an 80% overlap. The same preprocessing steps, including feature extraction and normalization, were applied to the test data. The CNN model demonstrated exceptional performance during the testing phase. For the *Printing* state, a test file containing 1785 segments was evaluated. All 1785 segments were correctly classified as *Printing*, achieving a precision, recall, and F1-Score of 1.00. Similarly, for the *Off* state, a separate test file containing 1922 segments was used. The model correctly classified all 1922 segments, achieving the same perfect metrics. The confusion matrix for both test files reflected zero misclassifications, highlighting the model's reliability.

Table 3. Classification Report of the CNN Model

Label	Precision	Recall	F1-Score	Support
0 (Off)	1.00	1.00	1.00	1259
1 (Printing)	1.00	1.00	1.00	1263
Accuracy	100 % (2522)			
Macro Avg	1.00	1.00	1.00	2522
Weighted Avg	1.00	1.00	1.00	2522

The following key observations can be drawn from the results: The model achieved an overall accuracy of 100% across all tested states, metrics such as precision, recall, and F1-Score were consistently 1.00 for both the *Printing* and *Off* states, confirming the model's effectiveness in correctly identifying machine states. These results validate the model's ability to generalize to unseen data, showcasing its applicability in real-world monitoring scenarios. These findings emphasize that the CNN model is not only robust but also highly accurate in classifying machine operational states based on sound data. Furthermore, the reliability of these metrics demonstrates the potential for deploying this methodology in practical industrial environments. The potential applications of this research extend to real-world scenarios where sound-based monitoring systems can play a vital role. For instance, in industrial settings, a 100% accurate classification system ensures efficient monitoring and prevents downtime by promptly identifying machine states. It also enhances safety by enabling real-time detection of operational anomalies, which can significantly reduce the risk of accidents or damage. As additional states such as "Cooling," "Bending," or anomalous conditions are incorporated into the dataset, and as the model is refined with further feature extraction, the system could enhance its ability to detect and classify a broader range of operational states. This progress suggests the potential for developing real-time anomaly detection systems that autonomously mitigate risks in industrial environments. In critical conditions, such as overheating, these systems could rapidly detect anomalies and respond effectively, thus preventing significant accidents. Such advancements could be integrated into an IoT framework, enabling intelligent, adaptive, and automated monitoring systems. Additionally, with further advancements in feature extraction and CNN architecture design, this methodology could evolve to identify even more details of machine states, such as detecting specific operational layers or stages within a process. For instance, in multi-layered processes like additive manufacturing or CNC machining, the system could potentially discern individual layers being processed, providing more detailed insights into machine operations. This capability would not only improve monitoring precision but also offer valuable data for process optimization, ensuring higher productivity and quality in industrial environments.

5 Conclusion

This study successfully revalidated the effectiveness of sound sensing as a robust method for machine monitoring by employing a Convolutional Neural Network (CNN) to classify the operational states of the Renishaw AM400 Additive Manufacturing machine. The research began by identifying the practical challenges of machine monitoring in industrial environments and selecting sound as an alternative sensing modality due to its affordability, non-invasiveness, and ease of deployment. A custom sound sensor was developed and deployed to collect audio data representing the *Printing* and *Off* states of the Renishaw AM400 machine. The data underwent preprocessing to remove irrelevant noise, segmentation into 1-second frames, and extraction of key features such as RMS, spectral centroid, spectral bandwidth, FFT energy, and frequency band energy. The processed dataset was then used to train a CNN model with advanced techniques like early stopping and dropout to prevent overfitting. Through extensive testing, the model demonstrated a perfect classification accuracy of 100%, validating its robustness and reliability.

6 Reflection

Through this research, I have gained a deeper understanding of the operation and specifications of various CNC machines and Additive Manufacturing machines. This knowledge will undoubtedly be invaluable for future endeavors involving industrial machines, whether in research or practical applications. Additionally, I have come to appreciate the significance of monitoring systems and the various approaches required to overcome the challenges associated with their implementation. This research allowed me to critically evaluate how to bridge these gaps effectively. Reading multiple academic papers also provided valuable insights into handling data in a formalized research context and ensuring the credibility of experimental results. Furthermore, I had the opportunity to observe how Smart Manufacturing has evolved beyond traditional manufacturing, achieving harmony between human and system integration while steadily advancing. This project also served as a platform to revisit and deepen my understanding of deep learning, particularly CNN models. Moving forward, I aspire to extend the outcomes of this research to develop systems capable of accurately distinguishing anomalies or additional states. This would bring me closer to implementing a real-time sound-based monitoring system that can proactively mitigate risks.

In the future, I am interested in exploring the potential applications of sound monitoring in the aerospace industry, as it aligns well with my personal background. Moreover, there have been efforts to study sound-based monitoring in this field. For example, *Real-time identification of aircraft sound events* [8] provides valuable insights into this area. Attaching sound sensors to various locations on noisy aircraft could potentially separate noise from meaningful signals, enabling anomaly detection that is otherwise impossible with software alone. This idea has the potential to replace human intervention with automated recognition systems, paving the way for broader applications in other industries. By branching out from this research, I aim to investigate various opportunities for advancing sound-based monitoring systems in diverse domains.

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