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IoT Signal Classification Using CNN over 5G for Industrial Fault Detection

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Abstract

Rapid advancement of the 5G networks and the World Wide Web has made remarkable improvement in the concepts of real-time data gathering and processing for the industrial applications. Especially in terms of industrial monitoring and defect detection where IoT signal processing is very essential, reducing downtime during operations, most of the old-age systems depend very heavily on manual detection methods or scant data analytics that leave many breakdowns unidentified, increasing the costs of maintenance. Old technologies were literally far behind in terms of accuracy and real-time applications required in any modern industrial setting. In this research work proposes a real-time IoT signal-processing framework for machine fault detection based on CNNs. Low-latency data transmission is facilitated by 5G networks so that fast analysis and decision-making can be done. The classification model based on CNN offered an accuracy of 95.2%, while precision was 93.8% and recall was 94.5% with respect to a latency of only 35 ms. This work overcomes the limitations of existing systems by allowing continuous automated fault detection, thereby increasing the reliability of the system and minimizing downtime. The proposed method offers industrial sector applications enhanced predictive maintenance by utilizing intelligent AI and high-end 5G communication.

Keywords: IoT, 5G, Signal Processing, CNN, Fault Detection, Edge Computing

1. Introduction

Signal processing from IoT through 5G networks has transformed industries by enabling real-time monitoring and analysis of large volumes of sensor data [1]. IoT connects devices which emit continuous signals, such as temperature, sound, and vibrations, which can be interpreted to provide useful information for defect diagnosis and predictive maintenance [2]. This process is greatly aided by 5G, providing high-speed, low-latency connectivity for quicker data transfer and significantly faster decision-making [3]. The combined approach enables more efficient and automated systems to take action against impending problems for increased operational efficiencies and decreased downtimes [4]. Advanced signal processing techniques ensure that data from the sensors are interpreted with precision, making it suitable for a number of critical applications, such as smart factory automation [5].The past methodologies adopted in fault detection comprise planned maintenance, human inspection, sparse data collection, and hence this system gets delayed in fault detection and there hasn't been sufficient time for recovery [6]. These older systems certainly do not suit modern-day high-demand businesses, as they generally do not incorporate any real-time capabilities to prompt any suitable reaction when equipment issues arise [7]. In most instances, newer systems are not capable of efficiently processing alarm data within a few seconds, which directly impacts the application of these systems in fault detection [8]. Not only this, but people also refrain from using contemporary communication technology like 5G, which boasts high-speed and low latency data throughput and hampers speedy decision making [9]. Adverse and condemned to obtain intelligent, faster, and cost-effective methods of linking IoT sensors, AI models, and 5G networks are rising in the demand of predictive maintenance and defect detection [10].

The limitations of existing fault detection systems stem from their reliance on conventional methods that often lead to inefficient handling of vast amounts of sensor data, excessive downtime, and delayed identification [11]. Such systems suffer from poor data communication and decision-making on account of their inability to provide real-time solutions and do not exploit certain modern technologies, like 5G networks [12]. Our approach adopts an integration of IoT signal processing, CNN-based classification models, and 5G for real-time analysis with low latency; in doing so, we overcome the noted limitations [13]. This approach ensures better reliability of the system, increased accuracy, and faster fault detection [14]. By developing the system for continuous automated fault detection with real-time decision-making capability, the proposed work leads to more efficient industrial systems with reduced downtime [15]. Recent advances in edge computing complement 5G to further reduce latency and improve data processing at the source [16]. Machine learning models trained on historical sensor data can identify subtle fault signatures that human operators might miss [17]. The adoption of AI-enabled predictive maintenance systems is becoming a key driver in Industry 4.0 transformations [18]. Moreover, cloud-based platforms offer scalable storage and computing resources for managing the massive datasets generated by IoT devices [19]. Real-time dashboards and alert systems enhance the ability of operators to make quick and informed decisions [20]. Security concerns around IoT and 5G integration must be addressed through robust encryption and authentication protocols [21]. Future research is expected to focus on the fusion of multi-modal sensor data using deep learning to further enhance fault detection capabilities [22].

1.1 Problem statement

The increasing complexity and demand for predictive maintenance in the industrial systems need effective and accurate technologies for real-time problem detection [23]. Conventional systems for machine defect detection usually employ manual inspections or limited data analysis with delayed detection and, hence, more downtime [24]. With the advent of IoT sensors and 5G communication, strong low-latency solutions are required for continuous monitoring and evaluation of machine health [25]. Thus, this research aims to propose an example of a real-time IoT signal processing framework for fault classification using CNNs, to enable rapid, accurate problem detection [26]. The proposed solution utilizes the capabilities of 5G networks to ensure that effective data transmission and decision-making are accomplished with high-speed, low-latency communication [27]. Improving predictive maintenance by automating defect identification minimizes potentially long operating downtimes and thereby enhances system reliability [28]. Additional integration of AI and edge computing will further optimize real-time analytics and fault detection capabilities [29]. Future advancements should focus on scalable architectures to manage the increasing data volume from industrial IoT deployments [30].

1.2 Objective

1. Design a framework for real-time IoT signal processing using CNNs to detect industrial faults.
2. Utilize 5G networks to transmit data with reduced latency for effective signal analysis.
3. Apply sophisticated CNN-based models to classify the machine's health condition (normal vs. defective).
4. Evaluate the accuracy, latency, and operational efficiency of the system.

The rest of the paper is organized as follows. Section 1 with the introduction. Section 2 will discuss the Theoretical Background. Section 3 presents the Methodology and Section 4 highlights the results. Section 5 concludes.

2. Literature review

Signal sparsity and its related algorithms can drive creativity in designing new 5G systems, as has been illustrated by describing appropriate situations around which such signals may occur naturally in 5G wireless systems [31]. They gave much emphasis to applications in the context of cloud radio access networks, compressive channel-source network coding, embedded security, and Multiple Input Multiple Output (MIMO) random access [32]. The latest type of 5G Intelligent Internet of Things (5G I-IoT), introduced by Wang *et al.*, uses big data mining, deep learning, and reinforcement learning to perform efficient data treatment with an optimized communication channel, achieving appreciable improvements in QoS and channel utilization [33]. 3GPP inexpensive fixed in band layer-3 Relay Nodes (RNs) for Internet of Things traffic in 5G networks were discussed by Javaid *et al.*, along with the development of an analytical model for maximizing the utilization of radio resources [34]. The practicality of this concept was validated by illustrating the efficiency of multiplexing IoT data packets for simultaneous transmission by multiple devices accessing common frequency resource blocks [35]. For catering to the high-traffic and low-latency demands of IoT and M2M communication, stress on multi-Gbps technologies that are expected in the future 5G networks while pinpointing the need for very significant changes such as deployment of millimetre-wave band for small cell application [36]. The multiband cooperative spectrum sensing and resource allocation framework for IoT in cognitive 5G networks was elaborated while highlighting cross-layer reconfiguration use for enabling the dynamic allocation of resources and the energy-saving potential [37]. In the context of the integration of multiple networks in the IIoT, the need for wearable healthcare systems to be low power and high accuracy was emphasized; also stressed was the importance of self-organizing summarized recent developments in signal processing techniques pertinent to 5G, such as modulation, beamforming, and cloud computing [38]. In his account of the development of wireless cellular networks, Lee gave special importance to the transition from 4G to 5G and the expected enhancements of eMBB, mMTC, and URLLC in fulfilling requirements from machine-to-machine and Internet of Things communications while focusing on appropriate radio numerology that would allow for high connection densities with short, bursty packet transmissions [39].

Proposed a frame structure for 5G IoT communications, examined the deployment of millimetre-wave bands in 5G networks for IoT applications, and showed that multimode operation needs other frequency bands to support IoT applications effectively [40]. To achieve energy-efficient working in 5G IoT systems, an integrating topology, which essentially involves mixing wired and wireless components, was proposed [41]. The 5G advanced wireless access network architecture H-CRAN was presented, which deals with resource allocation and energy harvesting issues while exploiting cloud computing for large-scale cooperative processing [42]. Recent studies highlight the importance of AI integration with 5G for intelligent resource allocation and enhanced network management [43]. Machine learning-based adaptive beamforming techniques improve signal quality and reduce interference in dense IoT environments [44]. Reinforcement learning algorithms have been proposed to optimize spectrum allocation dynamically in cognitive 5G networks [45]. Blockchain technology combined with 5G enhances security and privacy for distributed IoT systems [46]. Edge computing plays a crucial role in reducing latency and processing data closer to IoT devices in 5G architectures [47]. Deep learning models applied in 5G enable predictive maintenance and fault detection in industrial IoT [48]. Efficient handover strategies using AI ensure seamless connectivity in mobile 5G environments [49]. The combination of massive MIMO and millimetre-wave technologies enhances data throughput and connection density in 5G IoT applications [50]. Network slicing in 5G allows tailored services for diverse IoT use cases, improving QoS and resource utilization [51]. Finally, the convergence of AI, IoT, and 5G is paving the way for smarter cities and autonomous systems [52].

3. Proposed methodology

The complete process of signal processing in IoT before defect detection using a 5G CNN is shown in the diagram in Fig 1. The first stage of the process pertains to various sensor signals, including event-related signals, camera/video signals, and raw sensor signals, which will be subjected to signal processing. These signals are then input into the system to be cleaned and normalized, thus ensuring quality and consistency. This is the first time that the Wavelet Transform has been successfully applied to achieve highly qualified time-frequency analysis by extracting important signal features.

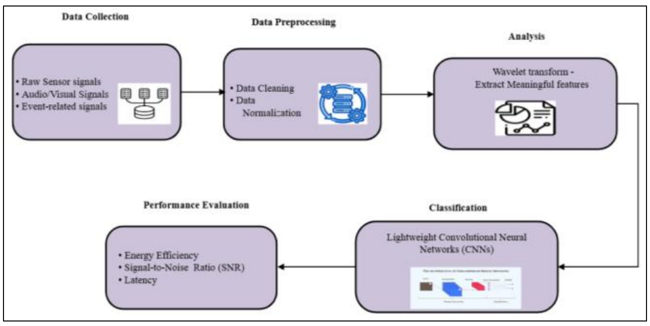

Fig 1: Workflow of IoT Signal Processing and Fault Detection Using CNNs over 5G

Lightweight Convolutional Neural Networks (CNNs) are then being trained using these features for the classification of data. The system also evaluates energy economy, latency, and signal-to-noise ratio (SNR) so as to ensure optimal performance, especially for detecting problems in real time. This combined strategy significantly improves the performance of the system in terms of accuracy, reliability, and speed, thus perfectly tailored for an industrial defect detection setup.

3.1 Data Collection

A MEMS-based accelerometer gives real-time vibration readings mounted on industrial machinery. These sensors transmit time-series data over a 5G network to the edge or cloud servers, ensuring fast and low-latency connectivity for processing and analysis. On the general note, any raw signal received at any moment t can be expressed mathematically as follows:

$$o(t) = m(t) + a(t) \tag{1}$$

Wherein the observed signal is $o(t)$, the machine-generated signal is $m(t)$, and the other component comprising the additive noise in the measurement is $a(t)$.

3.2 Signal Preprocessing

To ensure that the data quality is maintained, some preprocessing procedures are done over the signals. First, applying Butterworth filter removes undesirable high-frequency components from noise. Improved performances of the classification model are achieved after normalizing the signal using Min-Max scaling bringing all values within the same range. This is the normalization:

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{2}$$

At last, the signal is divided into fixed-size time frames to prepare it for feature extraction and analysis.

3.3 Feature Extraction using Wavelet Transform

Preprocessed signals are converted into a time-frequency representation via a discrete wavelet transform, which captures important transient features that are almost invisible in either the time or frequency domain by themselves. A signal x(t) has the following definition for its discrete wavelet transform (DWT).

$$W(i, n) = \int x(t) \cdot \psi_{i,n}(t)dt \tag{3}$$

Here, i is the scale related to frequency, n is the position related to time, and $\psi_{i,n}(t)$is the wavelet function scaled and shifted as per the rules of the definition.

3.4 Signal Classification using CNN

The thin 1D convolutional neural network (CNN) that (a) accepts wavelet transformed signal features and processes them for classification. CNN is also well-suited for learning spatial and temporal patterns from sequential inputs such as vibration signals. The convolution layer is the first major operation in any CNN, extracting local characteristics from an input signal using a voluntary collection of learnable filters. The mathematical expression for the operation is:

$$m_j = f\left(\sum_{i=1}^{x} m_{j+i} \cdot w_i + a\right) \tag{4}$$

where a is the bias term, f is the activation function (usually ReLU - Rectified Linear Unit), w is the filter (or kernel), and x is the input signal. After this, a pooling layer is introduced, reducing the size of the spatial dimension and representation. For example, the maximum value is picked from a particular window of input as indicated by:

$$m_i = max(x_i, x_{i+1}, \dots, x_{i+p}) \quad (5)$$

The final feature map is flattened and passed through fully connected layers after numerous convolution and pooling layers. The softmax function is then applied to the final output, which transforms the raw score outputs into probabilities of the classes.

$$\hat{m} = \text{softmax}(Wx + a) \quad (6)$$

In this case, $\hat{m}$ stands for the expected probability distribution of target classes, which allows the categorization of the signal into normal or defective by the CNN.
Performance evaluation is done once the CNN model is deployed on cloud servers or edge devices.

4. Results and discussions

Table 1 presents the performance evaluation metrics of the proposed CNN-based IoT signal processing system on a 5G network. Our model successfully classified vibration signals with an impressive 95.2% accuracy. The precision (93.8%) and recall (94.5%) figures show the model's success in minimizing false positives and false negatives. The model is quite balanced in recall and precision, as demonstrated by its F1-score of 94.1%. The system has near-real-time processing capabilities due to a very low latency of just 35 ms. With a throughput of 250 signals per second, it efficiently handles big data streams. The 22 dB signal-to-noise ratio is strong evidence for good preprocessing. The model is well-suited for IoT applications given its light weight (8.4 MB) and a mere 1.2 W consumption on an edge device.

Table 1: CNN-Based IoT Signal Processing Performance Metrics

Metric	Accuracy	Precision	Recall	F1-Score	Latency	Throughput	Signal-to-Noise Ratio	Model Size	Energy Consumption
Value	95.20%	93.80%	94.50%	94.10%	35 ms	250 signals/sec	22 dB	8.4 MB	1.2 W (edge)

Fig 2 shows the training profile of the CNN model trained for 10 epochs; it also depicts performance variances like accuracy against loss. Overall, the learning performance of this model is very good; it initiated with an accuracy of 95.1%, gradually increased, and finally reached 96.2%.Simultaneously, the loss continues to fall free in value from 0.20 to 0.08, signifying that optimization of the model weights has taken place successfully. Underfitting and overfitting are also ruled out since accuracy rises consistently as loss decreases. This pattern attests to the capabilities of the CNN model as well as its ability to classify signals accurately. The figure also indicates how rapidly the model reaches convergence in a few epochs, thus qualifying it for real-time applications in the Internet of Things.

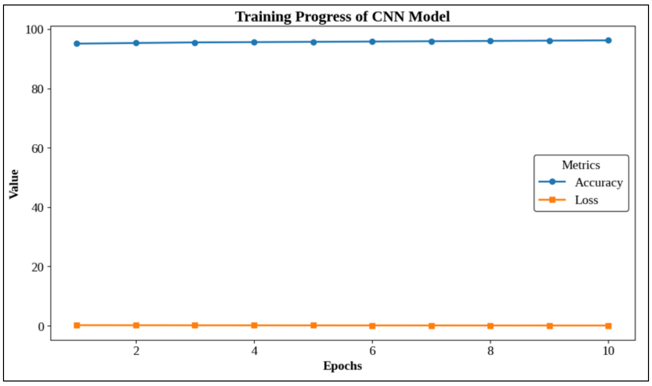

Fig 2: Epoch-wise Accuracy and Loss During CNN Model Training

Fig 3 displays the performance metrics of the proposed CNN-based IoT signal processing system over a 5G network. The model's classification performance indicated reliable defective detection with an accuracy of 95.2%, a precision of 93.8%, and a recall of 94.5%. The F1-score of 94.1% reveals that the recall and precision are well-matched. Also, while low latency (35 ms) is maintained, high throughput (250 signals/sec) validates its usefulness for applications requiring near real-time performance.

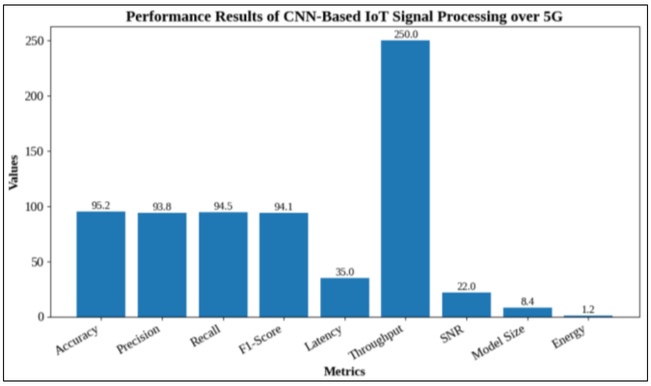

Fig 3: Performance Metrics of CNN-Based IoT Signal Processing over 5G

A Signal-to-Noise Ratio (SNR) of 22 dB represents clear signal and efficient preprocessing. Moreover, the small size of the model (8.4 MB) and its low energy usage (1.2 W) demonstrates its efficacy for edge deployment in Internet of Things environments.

5. Conclusion

This work demonstrates how CNNs integrate with 5G for real-time, IoT data processing to detect faults in manufacturing processes. Introducing ultra-low latencies (35 ms) with remarkable classification accuracy (95.2%) makes condition monitoring for machines efficient. 5G enhances decision-making with minimal communication latencies and very fast data transmissions. The performance of the model is, however, limited by the complicacy of real-world business problem scenarios, and the sensor quality captures some phenomena. It is also possible to bring additional sensor modalities (such as temperature and sound) into the model. Improve the model for more complicated fault kinds, and future research should work on scaling the current system into larger industrial contexts, with an understanding that a greater variety of different kinds of equipment will have to be considered.

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