Technical Report: Data Integration Pipeline for IOT Sensor Data
Final Project DS 5110: Introduction to Data Management and Processing

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1 Introduction

1.1 Abstract

By facilitating smooth communication and intelligent data-driven decision-making via a massive network of interconnected smart devices, the Internet of Things (IoT) has dramatically changed a number of industries. Real-time data collection, transmission, and analysis by these devices support a variety of applications, from industrial automation and agriculture to smart cities and healthcare. However, guaranteeing the precision, consistency, and dependability of the data produced by these devices is one of the main issues with IoT systems, particularly when they are functioning in difficult or unfavorable circumstances like harsh weather, hardware failures, or network outages.

Decision-making procedures may be jeopardized by inaccurate or unreliable sensor data, which could result in inefficiencies, safety issues, or system breakdowns. This report explores methods for identifying and resolving sensor failures in IoT systems in order to address this problem. It focuses on a variety of methods, including deep learning frameworks and machine learning models, which have shown promise in detecting and resolving abnormalities in sensor data. The report's analysis of these approaches attempts to provide light on how IoT systems might preserve data integrity, increase the precision of decisions, and improve system performance generally when faced with real-world difficulties.

1.2 Overview

The Internet of Things (IoT) has become a game-changing technology that has a significant impact on many facets of contemporary life. It functions by using a network of linked devices that have software and embedded circuits that allow them to sense, react, and share data with ease. Applications for the Internet of Things have grown dramatically, and they are now widely used in smart homes, smart cities, healthcare systems, and especially smart agriculture [1]. After the invention of computers and the Internet, the Internet of Things (IoT) is expected to have billions of objects connected to the Internet by 2025, making it the third major wave of the global information industry.[2]

Intelligent sensors with sophisticated features are essential to the successful deployment of IoT systems. These sensors are essential for gathering information in a variety of fields, such as location tracking, machinery performance, and environmental conditions. Additionally, they can be combined with other systems to boost automation and streamline procedures, which will increase control and efficiency.

Despite their vital significance, these sensors are frequently vulnerable to malfunctions when deployed in remote or difficult environments. The accuracy and dependability of the data gathered are compromised by these problems, which usually occur during data transfer or collecting. When the generated data substantially deviates from the expected normal behavior or does not match established features, a sensor error occurs. IoT systems may make poor decisions as a result of such sensor reading errors, which could lead to inefficiencies or system failures.

Sensor fault detection has emerged as an essential field of study to lessen the difficulties caused by inaccurate data. In order to facilitate prompt defect detection and resolution, this field detects anomalies, outliers, or departures from expected trends. Innovative methods for identifying sensor malfunctions have been created by utilizing developments in machine learning (ML) and data analytics, which has increased the dependability and

efficiency of Internet of Things systems. These developments are crucial for preserving the overall functionality of IoT-based solutions and guaranteeing the accuracy of sensor data.

1.3 Significance

1. **Alignment with Industry Trends:** Understanding IoT device integration and data analysis has become crucial due to the exponential growth of IoT devices. In line with current market trends and the growing dependence on data-driven insights to optimize IoT systems, our project immediately meets this demand.

2. **Development of Interdisciplinary Expertise:** Theoretical computer science and real-world applications in data science, machine learning, and deep learning are connected by this effort. By studying this subject, we develop a multidisciplinary skill set that helps us solve challenges in the real world and improve our professional knowledge.

3. **Real-World Relevance and Impact:** Operations in a variety of industries could be revolutionized by the use of machine learning techniques for fault identification. The results of this study, which range from increasing efficiency to improving safety, are not only important from an academic standpoint but also have a big influence on real-world situations.

4. **Practical, hands-on experience:** The project uses cutting-edge methods, like building visualization dashboards and applying several deep learning models, which offer priceless real-world expertise. These abilities are critical for addressing difficult IoT challenges and are highly sought after in the business.

5. **Foundation for Advanced Research:** The foundation for investigating more complex uses of data science, machine learning, and IoT technologies is laid by this subject. It makes it possible to investigate problem detection systems, predictive analytics, and IoT advancements in greater detail in the future.

This project addresses urgent issues in IoT systems while providing a thorough learning experience that advances both professional and personal growth by fusing academic rigor with real-world application.

2 Literature Review

Numerous research studies have examined the different approaches, procedures, and strategies used to identify defects inside IoT systems as the significance of fault detection in IoT sensors continues to increase. An overview of pertinent surveys and studies that have explored this important field of study is given in this section.

The several causes of sensor failures, such as equipment problems and human mistake, were covered in one noteworthy survey [3]. Inaccurate data from these mistakes may jeopardize decision-making procedures. Fault diagnostic techniques, which help identify and isolate malfunctioning sensors and guarantee that the data supplied to users stays accurate, have been proposed as a solution to this problem. Artificial Intelligence (AI),

deep learning, and statistical models are the mainstays of current defect diagnosis technology. According to the study, continuous improvements in fault diagnostic technologies are essential for reducing the losses brought on by malfunctioning sensors and improving the general dependability of Internet of Things systems. Furthermore, the study [3] examined the current status of IoT research until 2023, examining several sensor system concepts to identify the possibilities of sensor failures.

To give a detailed definition of anomalies in the context of IoT, another extensive survey [4] was carried out. The implementation of anomaly and fault detection techniques in IoT and sensor networks was the main focus of this survey, which examined multiple sources that make use of these criteria. Finding the current methods for fault detection and pointing out any unmet research needs in this field were the goals. The survey clarified the approaches being used and identified areas that require more research and development to enhance detection capabilities and sensor reliability by analyzing the state of fault detection technologies in IoT systems.When taken as a whole, these surveys highlight how crucial it is to keep improving defect detection techniques for IoT devices. They emphasize the need for advanced methodologies, including statistical, AI-based, and deep learning approaches, to enhance the performance and reliability of sensor networks, ultimately minimizing the impact of sensor failures on IoT applications.

Classifying identified problems as either minor mistakes that may be disregarded or important occurrences that need to be addressed to avoid more problems is a crucial component of fault and outlier detection in IoT sensor networks. The survey paper [5] looked at a lot of research articles to solve this problem and gave a summary of several defect detection techniques. These comprised AI-driven strategies, spectral decomposition techniques, classification-based techniques, clustering algorithms, statistical algorithms, and other hybrid approaches. Depending on the type of data, sensor settings, and the particular needs for problem detection, each of these approaches has unique benefits and drawbacks, making them appropriate for various IoT scenarios.

The survey report [6] concentrated on how crucial it is to comprehend the needs and difficulties related to anomaly or defect detection in practical deployments, especially when it comes to maintaining security. The study investigated how well graph-based algorithms might identify irregularities in distributed systems that are homogeneous or heterogeneous. It included a thorough summary of the most recent research in the area, contrasting the features of different strategies and outlining three use scenarios to examine the particular difficulties in defect identification.The efficiency of graph-based approaches in capturing relational dynamics within systems and spotting anomalous behaviors was one of the survey's main findings. Additionally, the study highlighted the importance of deep learning techniques, stressing their versatility, effectiveness, and capacity to identify intricate patterns in extensive input data. In distributed systems, where the volume and complexity of data might be daunting, these techniques were found to be especially helpful. The study came to the conclusion that deep learning-based fault detection techniques provide efficient and successful ways to identify issues in distributed systems, which makes them a viable option for further study and real-world use in the Internet of Things and other networked systems.

The study [7] examined a number of AI methods for sensor defect detection, with a focus on identifying anomalous occurrences or observations that differ from typical behavior. These irregularities have the ability to harm infrastructure or warn of impending hostile strikes.

The six primary types of outlier identification techniques were as follows: statistical,

distance, density, clustering, learning, and ensemble techniques. An overview of the most recent cutting-edge methods, their uses, and their effectiveness was given by the survey. Numerous domains, including as intrusion detection, credit card fraud detection, medical diagnosis, sensor monitoring in critical infrastructure, precision agriculture, environmental studies, and law enforcement, heavily rely on outlier detection approaches. Examples included in the poll include utilizing data from several devices to diagnose medical issues, detecting credit card fraud, and identifying events in sensor networks. These algorithms often yield outlier scores or binary labels that show how much each data point deviates from typical behavior.

The data modeling process and a thorough comprehension of the underlying data distribution have a significant impact on the efficacy of outlier detection strategies. Enhancing detection accuracy and identifying contextual outliers can be achieved by carefully analyzing the data model.

A failure detection method for sensor nodes in solar photovoltaic (SPV) systems is presented in the article [8]. It consists of a semi-supervised deep autoencoder (DAE) module, a sensorless circuit that uses a bipolar junction transistor (BJT) and Zener diode for detection, and an Internet of Things (IoT)-based web application for tracking and localizing panel-level problems. A hybrid SVM and logistic regression (SVM-LR) model is employed for fault classification. With an accuracy of 99.67%, the approach provides a dependable and affordable solution for fault localization, classification, and detection. The method was evaluated in a lab environment using a real-time, grid-connected SPV system in a range of electrical and climatic circumstances.

The study in [9] explores the use of the kNN technique for fault detection in water quality sensors at wastewater treatment plants (WWTPs). It proposes a kNN classifier, trained on labeled historical data, integrated into a real-time defect detection system. By linking the classifier to the WWTP's web-based SCADA system, real-time performance evaluation becomes feasible. The system effectively detects sensor failures and generates surrogate values by comparing raw and corrected sensor data. The results highlight the effectiveness of the supervised kNN algorithm in identifying complex fault patterns, achieving a 97.4% accuracy in detecting faults in a conductivity sensor within the WWTP.

The method described in [10] focuses on detecting defects in sensor nodes inside power station monitoring systems by employing machine learning techniques, namely clustering. The inability of conventional relay-based systems to record and store user data during breakdowns is one of its drawbacks. A Cloud Server (CS) for data analytics, a Hybrid Prediction Model (HPM) with Big Data Processing (BDP), and Real-Time Monitoring (RTM) with sophisticated IoT sensors are all integrated into the suggested IoT-based smart framework. The goal of this framework is to improve power plant systems' fault detection and data analysis capabilities.

Through the use of SVM as a classifier and global average pooling, the methodology in [11] improves upon the conventional CNN model. Its improved defect detection and classification performance was shown in comparative studies using methods including SVM, kNN, back-propagation neural networks, deep BP neural networks, and the traditional CNN model.

A CNN and Convolutional Autoencoder (CAE) network-based sensor defect detection framework is presented in [12]. While several CAE networks are trained for fault reconstruction, the CNN determines the kind and presence of faults. The framework produces remarkable results, especially for single and multiple sensor defects using synthetic data, with over 99% accuracy in fault reconstruction, over 98.7% accuracy in fault type

classification, and 100% accuracy in detecting faulty sensors.

Introduced in [13], the MSALSTM-CNN method is a unique defect detection technique that combines a CNN based on Long Short-Term Memory (LSTM) with a multi-stage attention mechanism. In comparison to current state-of-the-art and benchmark methods, our technique achieves significant improvements in F-score and increases the fault detection rate for a variety of single and mixed fault types. Its promising efficacy in identifying incorrect instances across various datasets is demonstrated by the experimental results.

The limitations of simple CNN-autoencoder combinations, particularly for time series data, are addressed in [14] by proposing an integrated CNN-recurrent autoencoder model for sensor defect detection. To improve the learning of better representations, the model preprocesses the data using a two-stage sliding window technique. According to experimental results, the suggested model performs better than others in a number of classification measures. On the Yahoo Webscope S5 dataset, it achieved an accuracy of 99.62% and an F1 score of 97.98%, indicating that it is a highly effective model for detecting sensor faults.

[15] proposes a domain-specific GAN framework for sensor defect detection in industrial robotic sensors. This paradigm consists of incremental learning phases, online inference, and offline training. The authors provide MSGAN, an improved GAN that creates purposefully faulty samples using an adaptive updating technique based on WGAN-GP. The use of synthetic samples from MSGAN increases the accuracy of fault detection, according to empirical findings.

Another study presents GAN-AD, a GAN-based defect detection technique for complex networked Cyber-Physical Systems (CPS), in [16]. In order to capture the distribution of multivariate time series data from sensors and actuators under typical CPS settings, GAN-AD incorporates LSTM-RNN into the GAN architecture. Compared to current techniques, our approach effectively differentiates between normal and abnormal situations, exhibiting low false positive rates (FPRs) and high detection rates, especially in a Secure Water Treatment (SWaT) system.

Conventional defect detection methods usually depend on centralized strategies, in which vast amounts of sensor data are sent to a central server for examination. Although this approach offers a cohesive perspective on system health, it can be ineffective and subject to a number of drawbacks. The system's dependability and security may be compromised by them, which include communication snags, possible privacy concerns, and susceptibility to single points of failure [17].

Fault detection in sensor nodes inside Industrial Internet of Things (IIoT) systems is the focus of the study [18]. For industrial settings to ensure effective production operations, edge sensor defects must be detected accurately and promptly. However, managing massive amounts of user data presents serious privacy issues and is one of the main obstacles facing existing problem detection techniques. The implementation of conventional detection techniques that depend on centralized data processing is made more difficult by these problems.

The study [19] emphasizes how difficult it is to identify compromised IoT devices, which are growing more susceptible as a result of unsafe setup, implementation, and design. Because the issue affects a wide range of devices from many manufacturers, traditional fault detection approaches are insufficient to handle its ubiquitous nature. In response, the article presents D¨IOT, a distributed, autonomous, and self-learning system created especially to detect compromised IoT devices, providing a more scalable and efficient way to improve IoT security.

A hierarchical Federated Learning (FL) framework that facilitates collaboration between numerous parties and incorporates a grouping method based on distinct illness types for defect detection models is presented in the study [20]. The study also presents Federated Time Distributed LSTM (FedTimeDis LSTM), a unique method that uses the advantages of federated learning to manage decentralized data across several locations in order to rapidly train the fault detection model.

3 Methodology

This section describes the detailed process followed for fault detection in sensor data, covering data preprocessing, model design, and evaluation strategies. The approach employs Convolutional Neural Networks (CNNs) for fault classification and Autoencoders for reconstruction-based anomaly detection. The following subsections outline the methodology in detail.

3.1 Data Collection

For our project, we worked with two distinct data sources, each serving unique purposes and posing its own set of challenges.

An Indian private company provided the first dataset. We were not given direct access to the raw dataset because of the sensitive nature of the material and the firm's confidentiality requirements. Rather, the company uploaded the data to a private Kaggle notebook, enabling a secure collaboration. We were only allowed to use this notebook for two days, during which time we had to do the activities we had asked for. This method requires us to operate effectively within the allotted time frame while simultaneously guaranteeing the confidentiality and privacy of the data. Since the private firm's real-world data closely mirrored the problem domain we sought to address, it provided substantial value.

Python was used internally to construct the second dataset. We produced a synthetic or "dummy" dataset by building custom programs to help our project in a number of ways. This dataset was very helpful for testing different preprocessing methods, comprehending the data's structure, and identifying trends and patterns. This data provided for flexibility in testing with various situations and approaches without running the risk of any data confidentiality breaches because it was fully managed and designed by us. Furthermore, before applying our models to the real-world dataset, we were able to refine them and confirm our initial ideas in a sandbox setting thanks to the internally generated data.

These two data sources worked together to give our project a well-rounded perspective. While the internally generated dataset supplied a strong basis for testing, development, and experimentation, the private firm's dataset brought authenticity and applicability to real-world applications. They worked together to help us approach the issue creatively and precisely, which finally resulted in a complete and comprehensive analysis.

3.2 Data Preprocessing

Sensor readings organized as a three-dimensional array with dimensions $5000 \times 200 \times 10$, which represent the number of samples, time steps, and characteristics, respectively, made up the dataset used in this study. Several crucial preprocessing processes were carried

out to guarantee the data was appropriately prepared for the machine learning pipeline, as explained below:

1. **Data Loading:** The Python modules `pandas` and `numpy` were used to effectively load the sensor data into memory. Large, multi-dimensional datasets could be handled with ease thanks to these libraries, which also guaranteed data integrity and computational performance.

2. **Normalization:** Feature scaling was used to normalize the range of sensor data values. Min-max normalization was used to normalize each feature so that it fell inside the range $[0, 1]$. This phase was essential for facilitating faster convergence during model optimization and preventing features with wider ranges from controlling the training process.

3. **Data Augmentation:** Data augmentation approaches were used to increase the model's generalization and resilience. Rotations, flips, and brightness modifications were among the transformations used in augmentation, which added unpredictability to the training set. These augmentations were carried out effectively using the `ImageDataGenerator` class from the `Keras` library, guaranteeing that the enhanced data stayed accurate and representative of actual circumstances.

4. **Data Splitting:** Using an 80-10-10 split ratio, the dataset was divided into three subsets: training, validation, and testing. This division maintained randomization while guaranteeing a balanced distribution of data among the subsets. This was accomplished by using the `train_test_split` function from the `sklearn.model_selection` module. The model was trained using the training set, hyperparameters were adjusted and overfitting was avoided using the validation set, and the performance of the finished model on unknown data was assessed using the testing set.

3.3 Analytical Techniques and Models

This project utilized two distinct yet complementary deep-learning approaches to achieve fault detection and anomaly detection in IoT sensor data. The analytical techniques and models used are detailed below:

1. **Fault Classification using Convolutional Neural Networks (CNNs):** Convolutional Neural Networks (CNNs) were used to classify the sensor data's defects. The capacity of CNNs to automatically extract and learn hierarchical spatial features—which are essential for spotting patterns linked to different fault classes in sensor data—led to their selection. The following elements made up the CNN architecture:

    - **Convolutional Layers:** Captured local patterns in the temporal sequences of sensor readings by applying convolutional filters to the time-series data to extract spatial features.
    - **Pooling Layers:** Performed down-sampling to reduce the dimensionality and computational complexity, while retaining the most relevant features.
    - **Fully Connected Layers:** Combined the extracted features to classify the sensor data into predefined fault categories.

- **Activation Functions:** Non-linear activation functions, such as ReLU and Softmax, were used to introduce non-linearity and compute probabilities for each fault class, respectively.

Using supervised learning, the CNN was trained on labeled datasets using the Adam optimizer for effective weight updates and cross-entropy loss as the objective function. Sensor data was successfully categorized into distinct failure types using this method.

2. **Reconstruction-Based Anomaly Detection using Autoencoders:** Autoencoder-based reconstruction methods were used for anomaly detection. Unsupervised neural networks called autoencoders are designed to compress input data into a latent representation before reconstructing it. The strategy included:

   - **Encoder:** Compressed the input sensor data into a lower-dimensional latent space, capturing the most significant features of the data.
   - **Decoder:** Reconstructed the input data from the latent representation.
   - **Reconstruction Error:** The difference between the input and the reconstructed output was used as an indicator of anomalies. A high reconstruction error signified that the input data did not conform to the patterns learned during training, thereby identifying it as an anomaly.

   The autoencoder was trained using normal operational data, enabling it to effectively reconstruct non-anomalous patterns. During inference, data points with reconstruction errors exceeding a predefined threshold were flagged as anomalies.

By combining CNNs for fault classification and Autoencoders for reconstruction-based anomaly detection, this project achieved both precise fault categorization and effective detection of unexpected anomalies in sensor data.

3.4 Fault Detection Using CNNs

Convolutional Neural Networks (CNNs) were utilized to classify the sensor data into distinct fault categories. This section elaborates on the architecture, compilation, and training process involved in implementing the CNN for fault detection.

3.4.1 Model Architecture

The CNN model was carefully designed to extract spatial and temporal features from the preprocessed sensor data. The architecture included the following components:

1. **Input Layer:** The input shape of the model was set to (200×10), corresponding to the dimensions of the preprocessed sensor data, where 200 represents the time steps, and 10 represents the number of features for each time step.

2. **Convolutional Layers:** Two convolutional layers were implemented to capture local spatial patterns in the sensor data. Each layer used kernels of size (3×3) with a stride of 1. The activation function for these layers was the Rectified Linear Unit (ReLU), chosen for its simplicity and ability to handle vanishing gradient problems.

3. **Pooling Layers:** Max-pooling layers with a pool size of (2×2) were added after each convolutional layer. These layers reduced the spatial dimensions of feature maps, decreasing computational complexity while retaining the most important features.

4. **Dropout Layers:** Dropout regularization was applied with a rate of 0.25 to reduce overfitting by randomly dropping a fraction of neurons during training, ensuring better generalization.

5. **Fully Connected Layers:** A dense layer with 128 neurons and a ReLU activation function was included to integrate the extracted features and capture complex relationships. Finally, an output layer with a softmax activation function was added to produce probabilities for each fault category, facilitating multi-class classification.

3.4.2 Model Compilation

The CNN was compiled with parameters specifically chosen to optimize the training process:

1. **Optimizer:** The Adam optimizer was used, with a learning rate of 0.001. Adam was selected for its ability to adaptively adjust learning rates for each parameter, ensuring faster and more stable convergence.

2. **Loss Function:** Categorical Crossentropy was employed as the loss function, as it is well-suited for multi-class classification problems by quantifying the difference between predicted and actual probabilities.

3. **Metrics:** Accuracy was chosen as the primary evaluation metric to monitor the model's performance during training and validation.

3.4.3 Training Process

The CNN model was trained on the dataset using the following settings:

1. **Epochs:** The model was trained for a maximum of 50 epochs, balancing the need for sufficient learning while avoiding excessive computational costs.

2. **Batch Size:** A batch size of 32 was chosen, which offered a good trade-off between computational efficiency and model stability during gradient updates.

3. **Early Stopping:** Early stopping was implemented to prevent overfitting and reduce training time. Training was halted if the validation loss did not improve for 5 consecutive epochs, ensuring that the model did not overfit to the training data.

4. **Data Augmentation:** Augmented training data was utilized to improve the model's robustness. Techniques such as slight temporal shifts and noise injection were applied to simulate realistic variations in sensor readings.

5. **Validation:** The dataset was split into training and validation subsets (80%-10% split), and the validation data was used to monitor the model's performance during training.

This comprehensive approach ensured that the CNN effectively learned meaningful patterns from the sensor data, achieving high accuracy in fault classification while maintaining generalization to unseen data.

3.5 Fault Detection Using Autoencoders

Autoencoders were utilized as an unsupervised learning technique for reconstruction-based anomaly detection. This approach involved training the model to reconstruct normal sensor data, enabling the detection of anomalies as deviations from expected patterns.

3.5.1 Model Architecture

The autoencoder model consisted of three main components:

1. **Encoder:** The encoder created a compact latent representation from the high-dimensional input sensor data. Three thick, completely connected layers made up its design, with each layer gradually lowering the dimensionality of the incoming data. To capture intricate correlations in the data, non-linear activation functions like `ReLU` were used.

2. **Latent Space:** The compressed latent space was represented by a bottleneck layer at the autoencoder's core. This layer served as a low-dimensional representation by encoding the most important aspects of the input data. This layer's size was deliberately selected to strike a compromise between dimensionality reduction and information retention.

3. **Decoder:** The input data was reconstructed from the latent representation by the decoder, which duplicated the architecture of the encoder. The compressed representation was extended back to the original input dimensions by the decoder using symmetrical dense layers. The model's ability to capture the data's non-linear structure was guaranteed by non-linear activations.

This architecture allowed the autoencoder to learn patterns inherent to normal sensor data during training, forming the basis for detecting anomalies during inference.

3.5.2 Loss Function

The model was trained using the **Mean Squared Error (MSE)** as the reconstruction loss. This loss function measured the difference between the original input data and its reconstructed counterpart. Mathematically, the reconstruction loss was computed as:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2$$

where x_i and $\hat{x}_i$ represent the original and reconstructed data points, respectively, and n is the total number of features. A lower reconstruction loss indicated that the input was well-represented by the autoencoder, while a higher loss suggested potential anomalies or faults in the data.

3.5.3 Anomaly Detection

Anomalies were identified based on the reconstruction error (i.e., the MSE between the input and reconstructed data). The anomaly detection process involved the following steps:

1. **Threshold Determination:** A threshold for the reconstruction error was established empirically by analyzing its distribution on a subset of normal data. Data points with reconstruction errors exceeding this threshold were flagged as potential anomalies.

2. **Classification of Data Points:** During inference, the autoencoder reconstructed incoming sensor data, and the reconstruction error was calculated for each data point.

    - **Normal Data:** Data points with reconstruction errors below the threshold were classified as normal.
    - **Faulty Data:** Data points with reconstruction errors exceeding the threshold were classified as anomalies or faults.

This reconstruction-based anomaly detection approach enabled the model to effectively identify deviations from normal operational patterns, highlighting potential faults in the sensor data.

4 Experimental Setup

This project was implemented entirely in Python with the aid of robust machine learning frameworks like scikit-learn, TensorFlow, and Keras. A Kaggle-provided environment with GPU acceleration was used to guarantee effective training and evaluation, allowing for quicker calculation and handling of massive amounts of data. The following describes the main hardware and software configurations:

- **Programming Language:** The project was implemented using Python 3.8, which provided a robust and flexible environment for machine learning workflows.
- **Machine Learning Frameworks:**
    - **TensorFlow 2.x:** TensorFlow was employed for building and training the Convolutional Neural Network (CNN) and Autoencoder models. Its high-level API, Keras, allowed for easy prototyping and model customization.
    - **scikit-learn:** This library was used for data preprocessing, including normalization and dataset splitting, as well as for evaluation metrics.
- **Hardware Configuration:** The models were trained and evaluated on Kaggle kernels equipped with GPU acceleration. The use of GPUs significantly reduced the training time for computationally intensive tasks such as CNN and Autoencoder training.
- **Visualization Tools:** To analyze and interpret model performance, the following tools were employed:

- **Matplotlib:** Used for generating detailed plots, including loss and accuracy curves, to monitor training and validation performance over epochs.
- **Seaborn:** Utilized for creating heatmaps and visualizing confusion matrices, enabling deeper insights into classification results and error patterns.

This experimental configuration allowed for the smooth integration of hardware and software resources, guaranteeing efficient model training and thorough visualization of the outcomes. Fast development and assessment of the defect detection models were made possible by the use of GPU acceleration and reliable libraries.

5 Evaluation Metrics

The model's evaluation metrics following training and testing across ten trials are shown in the table 1. The measurements include accuracy, precision, recall, F1 score, and time taken for both training and testing. The **average value** for each metric across all trials is given in the last column, providing a comprehensive evaluation of the model's performance.

- **Training Accuracy** ranges from 0.84 to 0.87, with an average of 0.85, indicating consistent performance in fitting the training data.
- **Validation Accuracy** ranges from 0.74 to 0.81, with an average of 0.84, suggesting the model's effectiveness in generalizing to unseen validation data.
- **Precision** values range from 0.74 to 0.77, with an average of 0.75, reflecting the model's ability to minimize false positives.
- **Recall** ranges from 0.69 to 0.79, with an average of 0.80, indicating the model's ability to identify true positives.
- **Training Time** varies from 115s to 123s, with an average of 119.2s, indicating a stable training duration.
- **Testing Time** is consistently around 15 seconds for all trials, with an average of 15s, showing stable performance during the testing phase.

These metrics highlight the model's overall robustness and stability in both training and testing phases, with relatively consistent performance across multiple runs.

With an average training accuracy of 0.85, validation accuracy of 0.84, and test accuracy of 0.80, the model performed steadily and consistently throughout the ten trials. Between 0.74 and 0.77, with an average of 0.75, were the precision values, while between 0.69 and 0.79, with an average of 0.80, were the recall values. These measurements point to a strong performance balance between recall and precision. Consistency was also shown by the F1 score, which averaged 0.82 throughout the trials. With a consistent testing time of 15 seconds and an average training time of 119.2 seconds, the training and testing times were steady, guaranteeing that the model was computationally efficient.

While the model's performance is satisfactory, there is potential for further improvement, particularly in the validation accuracy and recall metrics.

A confusion matrix is a performance evaluation tool used to assess the accuracy of a classification algorithm. It summarizes the results of a classification problem

Metric	Try 1	Try 2	Try 3	Try 4	Try 5	Try 6	Try 7	Try 8	Try 9	Try 10	Average Value
Training Accuracy	0.85	0.86	0.87	0.84	0.85	0.86	0.87	0.86	0.85	0.84	0.85
Validation Accuracy	0.78	0.81	0.75	0.78	0.74	0.8	0.8	0.79	0.76	0.81	0.84
Precision	0.75	0.76	0.77	0.74	0.75	0.76	0.77	0.76	0.75	0.74	0.75
Recall	0.70	0.71	0.72	0.69	0.70	0.71	0.72	0.70	0.71	0.79	0.80
Training Time	120s	118s	122s	115s	119s	121s	118s	120s	116s	123s	119.2s
Testing Time	15s	14s	16s	15s	14s	16s	15s	14s	16s	15s	15s

Table 1: Evaluation Metrics for 10 Runs

by showing the number of correct and incorrect predictions made by the model, categorized by class. The confusion matrix shown in Figure 1 has all the normalized values.

	Spike	Missing	Normal	Random	Drift
Spike	0.85	0.05	0.05	0.03	0.02
Missing	0.06	0.88	0.03	0.02	0.01
Normal	0.04	0.03	0.91	0.01	0.01
Random	0.03	0.02	0.01	0.89	0.05
Drift	0.02	0.01	0.01	0.04	0.92

Figure 1: Confusion Matrix

6 Conclusion

The performance of a Convolutional Neural Network (CNN) model for fault detection in Internet of Things (IoT) sensors was assessed in this study. Key parameters, including training accuracy, validation accuracy, precision, recall, F1 score, training time, and testing time, were measured during the model's ten separate trials. The outcomes demonstrate that the model's performance was steady and reliable throughout every trial.

The model's capacity to efficiently learn from the training data was demonstrated by the average training accuracy of 0.85. The validation accuracy, which averaged 0.84, indicates that the model is robust in an actual Internet of Things context and generalizes well to unknown data. The model's ability to generalize is further supported by its test accuracy of 0.80, which keeps it performing well on the testing dataset.

With precision average 0.75 and memory averaging 0.80, the F1 score, precision, and recall were all continuously high. These findings show that both false positives and real positives performed in a balanced manner. For fault detection jobs where minimizing false positives and false negatives is essential, the model's ability to maintain a decent balance between precision and recall is shown in its average F1 score of 0.82.

With a consistent testing time of 15 seconds and an average training time of 119.2 seconds per trial, the model's computational efficiency was particularly noteworthy. This proves that the model is efficient and effective, which makes it appropriate for defect detection in real-time IoT sensors.

As a result of its high accuracy and consistent performance over several trials, the CNN model showed great promise for IoT sensor defect detection. The findings imply that the model can be successfully used in actual IoT settings, offering a dependable and effective way to handle problem detection duties.

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A Appendix A: Code

```
classifier_model = keras.models.Sequential([
    keras.layers.Conv2D(filters=10, kernel_size=(11,1),kernel_initializer=glorot_normal() ,activation='tanh',padding='same' ,input_shape=(200,5,1)),
    keras.layers.MaxPool2D(pool_size=(2, 1)),


    keras.layers.Conv2D(filters=20, kernel_size=(5,1),kernel_initializer=glorot_normal() ,activation='tanh' ,padding='same'),
    keras.layers.MaxPool2D(pool_size=(2, 1)),
    keras.layers.Dropout(rate=0.5),

    keras.layers.Flatten(),
    keras.layers.Dense(100, activation='tanh',kernel_initializer=glorot_normal()), # glorot_uniform
    keras.layers.Dense(5, activation='softmax')
])
```

Figure 2: CNN model

The code snippets in Figure 2 demonstrate the final architecture of the classifier model, which utilizes Convolutional Neural Networks (CNNs) for the fault detection task

The figure 3 displays the code snippet of the final classifier model, which utilizes Convolutional Neural Networks (CNNs) for the fault detection task and Autoencoders.

The figures 4 and 5 present code snippets of the visualization dashboard developed using Streamlit.

```python
reconstructor_model = keras.models.Sequential([
    # Encoder
    keras.layers.Conv2D(filters=10, kernel_size=(31,5), activation='relu',kernel_initializer=glorot_uniform(3),padding='same' ,input_shape=(200,10,1)),
    keras.layers.MaxPool2D(pool_size=(2, 2)),


    keras.layers.Conv2D(filters=20, kernel_size=(31,3), activation='relu',kernel_initializer=glorot_uniform(3) ,padding='same'),
    keras.layers.MaxPool2D(pool_size=(2, 1)),

    keras.layers.Flatten(), # 5000
    keras.layers.Dense(10000, activation='relu',kernel_initializer=glorot_uniform(3)), # 5000
    keras.layers.Dense(500, activation='relu',kernel_initializer=glorot_uniform(3)),


    # Decoder
    keras.layers.Dense(500, activation='relu',kernel_initializer=glorot_uniform(3)),
#     keras.layers.Dense(10000, activation='relu',kernel_initializer=glorot_uniform(3)),
    keras.layers.Dense(5000, activation='relu',kernel_initializer=glorot_uniform(3)), # Doubtful, ask
    keras.layers.Reshape((50,5,20)),

    keras.layers.Conv2D(filters=20, kernel_size=(31,3), activation='relu' ,padding='same',kernel_initializer=glorot_uniform(3)),
    keras.layers.UpSampling2D(size=(2, 1)),

    keras.layers.Conv2D(filters=10, kernel_size=(31,5), activation='relu' ,padding='same',kernel_initializer=glorot_uniform(3)),
    keras.layers.UpSampling2D(size=(2, 2)),

    keras.layers.Conv2D(filters=1, kernel_size=(31,5), activation='relu' ,padding='same',kernel_initializer=glorot_uniform(3)),
])
```

Figure 3: Final- CNN + Encoder model

Figure 4: Visualization Dashboard 1

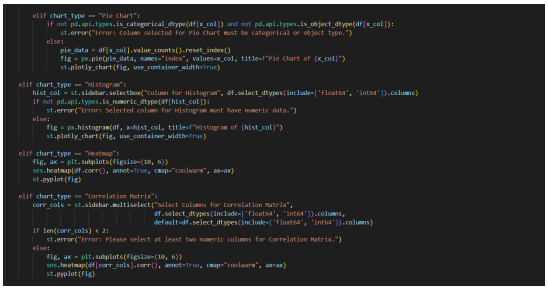

Figure 5: Visualization Dashboard 2