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A HIERARCHICAL ATTENTION MECHANISM FOR SENSOR DATA ANALYTICS IN INTERNET OF THINGS (IOT) APPLICATIONS

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ABSTRACT

The rapid proliferation of Internet of Things (IoT) technology has resulted in an exponential increase in sensor data generated by diverse connected devices. Extracting valuable insights from this vast and complex data has become a critical challenge, necessitating advanced analytics techniques. In this project, to improve sensors analysis of data in applications for the Internet of Things, we suggest a unique technique that combines a method of attention with Long Short-Term Memory (LSTM). The attention mechanism selectively focuses on relevant sensors and their readings, dynamically weighting their importance based on the context, allowing intricate trends and connections between dates in the data to be captured by the algorithm. Concurrently, LSTM excels at modeling sequential information, enabling accurate predictions and efficient anomaly detection. Extensive experimentation and performance evaluations are conducted to assess the efficacy of our approach, contrasting it with current practices. The outcomes show that our suggested technique produces improved predictions. accuracy, efficiency, scalability, and robustness to missing data, outperforming other approaches. The synergistic integration of attention mechanism and LSTM empowers IoT applications with deeper insights and more informed decision-making capabilities. This research highlights the potential of advanced analytics techniques in optimizing IoT systems, fostering data-driven innovation, and promoting efficient resource utilization across various industries, including smart manufacturing.

Keywords: *Internet Of Things, Sensor Data Analytics, Attention Mechanism, Hierarchical Attention, Smart Building.*

1. INTRODUCTION

The amount of information collected by sensors created across multiple areas has increased exponentially as a result of the fast spread of the Internet of Things, or IoT, technology and its incorporation with sensors-equipped equipment. In IoT applications, sensor data analytics plays a pivotal role in extracting meaningful insights, making accurate predictions, and enabling data-driven decision-making [1]. However, the dynamic and complex nature of sensor data, coupled with the multi-sensor and multi-level structure, presents significant challenges for conventional data analysis methods. The proposed method leverages a hierarchical attention mechanism to selectively focus on relevant sensors and their readings, effectively capturing the temporal dependencies and complex patterns present in the sensor data. By incorporating this attention mechanism into the data analysis process, The research improve the efficiency and accuracy of prediction tasks, anomaly detection, and other analytical tasks, contributing to more robust and insightful IoT applications. The application of IoT in sensor data analytics spans diverse fields, revolutionizing industries worldwide. Environmental monitoring benefits from real-time data on air quality, temperature, and pollution levels, aiding climate change monitoring and disaster management. Healthcare leverages remote patient monitoring through wearable devices, while smart cities optimize operations with sensors tracking traffic, waste management, and energy consumption. Industrial IoT enhances operational efficiency by monitoring machinery and predicting maintenance needs. Agriculture employs IoT sensors for precision farming, optimizing irrigation and crop yields. Energy management benefits from real-time data for better energy usage and integration of renewable sources. Asset tracking and management in logistics streamline supply chains. Predictive maintenance anticipates equipment failures, reducing downtime and costs. Smart home automation enables energy-efficient and secure household management. Water management uses IoT sensors to monitor water quality and levels, aiding conservation efforts. IoT empowers sensor data analytics across industries, providing valuable insights and facilitating data-driven decision-making.

Sensor data analytics refers to the process of extracting valuable insights and knowledge from the data generated by various sensors in the Internet of Things (IoT) and other data-driven systems. The rapid growth of connected devices and sensors has resulted in a massive influx of data, making it essential to analyze and interpret this data effectively [2]. Sensor data analytics involves applying various techniques, such as statistical methods, machine learning, and data mining, to process, clean, and interpret the data. The primary goal is to gain a deeper understanding of the sensor readings, detect patterns, anomalies, trends, and correlations, and make data-driven decisions based on the analysis. This field finds applications in various industries, including environmental monitoring, healthcare, smart cities, industrial automation, and more, where sensor data is crucial for monitoring, optimization, and predictive maintenance. By leveraging sensor data analytics, organizations can improve efficiency, reduce costs, enhance safety, and gain valuable insights for better decision-making and innovation. Attention mechanism-based LSTM refers to a model that combines the power of Long Short-Term Memory (LSTM) with an attention mechanism to enhance the analysis of sequential data, especially in problems requiring analysis of time sequences, picture closed-captioning or human language manufacturing, amongst others. The attention mechanism allows the model to focus on relevant parts of the input sequence or image while ignoring irrelevant information. In the context of LSTM, the attention mechanism dynamically weights the importance of different time steps or elements in the sequence, enabling the seamless to effectively capture long-range dependencies and complex patterns. The attention-gathering mechanism-based LSTM processes each input sequence in order to function step-by-step, and at each time step, it computes attention weights for all the time steps in the input sequence. These attention weights reflect the importance of each time step in the context of the current time step. The weighted sum of the input sequence elements, based on their attention weights, is then combined with the LSTM hidden state to generate a context vector. This context vector is used as the input to the LSTM at the current time step, allowing the model to focus on the most relevant information while making predictions. By incorporating the attention mechanism into LSTM, the model can selectively attend to crucial information, effectively handling long sequences and improving performance in tasks that require the understanding of complex relationships within the data. Attention mechanism-based LSTMs have been widely used in various domains, including machine translation, sentiment analysis, speech recognition, and more, showcasing their versatility and effectiveness in capturing intricate patterns in sequential data.

Attention mechanism for sensor data analytics is a powerful technique that selectively focuses on relevant information within the sensor data while filtering out noise and irrelevant details. It is inspired by the human cognitive process of paying attention to specific elements while processing information. In the context of sensor data analytics, attention mechanisms have gained significant attention in recent years due to their ability to enhance the accuracy and efficiency of various tasks, especially in Internet of Things (IoT) applications [3]. In IoT environments, data is collected from numerous sensors that monitor various aspects of the environment, such as temperature, humidity, pressure, motion, and more. This sensor data is often complex and high-dimensional, making it challenging to extract meaningful patterns and relationships. An attention

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mechanism comes into play by assigning different weights or importance to different sensors and their readings based on their relevance to the current context or task. Each sensor and its readings are associated with attention weights that reflect their importance for the current context. These weights are learned during the training process and can change dynamically as the context evolves or as the task requirements change [4]. By adaptively adjusting the attention weights, the model can focus on the most informative sensors and their readings while downplaying the significance of less relevant data [5]. This adaptability ensures that the model can effectively capture complex patterns and relationships within the sensor data. The mechanism of attention may be used in time-series sensor information over several time steps, enabling the model to detect spatial connections and recurring trends that may be crucial for accurate predictions or anomaly detection. Similar to attention mechanisms in deep learning, context-aware sensing assesses the current context or situation to determine which sensors are most relevant. The context may include factors like environmental conditions, user interactions, or the state of the system. Each sensor's data is associated with an attention weight that reflects its importance for the current context. Sensors with higher attention weights are given priority in data acquisition, while those with lower weights may be sampled less frequently or skipped altogether. The attention weights can change dynamically as the context evolves or as the task requirements change. Attention mechanisms play a crucial role in sensor data analytics, especially in IoT applications where the data is complex, dynamic, and high-dimensional [6]. The dynamic and intricate nature of sensor data is emblematic of the complexity inherent in our modern interconnected world. Sensors scattered across industries, environments, and applications capture data that ranges from environmental conditions to human health and industrial processes. Without effective means to analyze and extract meaning from this data, risk squandering the transformative potential of IoT. To harness the full scope of this potential, the suggested approach presents a pioneering solution: a hierarchical attention mechanism designed to selectively pinpoint relevant sensors and their readings. It captures the temporal intricacies and complex patterns that lie within sensor data. By selectively focusing on relevant sensors and readings, attention mechanisms enhance the model's ability to extract meaningful insights from the sensor data, leading to more accurate predictions, anomaly detection, and informed decision-making in various IoT scenarios. By considering the context of the current situation or environment, the model can adjust attention weights dynamically, leading to more adaptive and accurate analysis of sensor data in changing scenarios. Attention mechanisms are valuable for anomaly detection in sensor data. By highlighting deviations from normal patterns and giving attention to unusual sensor readings, the model can effectively detect anomalies and potential faults in IoT systems [7]. To illustrate the model's suitability for real-time processing, the research could provide specific use cases where the AM-LSTM model meets stringent latency constraints, such as real-time predictive maintenance in industrial IoT or immediate anomaly detection in autonomous vehicles. This research addresses the burgeoning challenges in the realm of sensor data analytics within Internet of Things (IoT) applications. The proliferation of sensors integrated with IoT technology has ushered in an era of vast data collection, necessitating advanced analytical approaches for meaningful insights and data-driven decision-making. The primary contribution lies in the development of a novel hierarchical attention mechanism tailored for the complexities of sensor data. This hierarchical attention mechanism strategically focuses on pertinent sensors and their readings, effectively capturing the intricate temporal dependencies and complex patterns inherent in sensor data. By seamlessly integrating this attention mechanism into the data analysis pipeline, this research significantly enhances the efficiency and accuracy of predictive tasks and anomaly detection, thus fortifying the foundation of robust and insightful IoT applications. The key contributions of the process are as follows,

- The research begins with extensive data collection from critical datasets FD001 and FD004, which serve as essential sources of sensor data for analysis.
- An LSTM (Long Short-Term Memory) structure is designed and implemented to effectively handle sensor data analytics. LSTM is chosen for its ability to capture sequential dependencies in the data.
- The proposed method integrates an attention mechanism intelligently with the LSTM. This attention mechanism is designed to focus on relevant sensors and their readings, enhancing the model's

ability to capture the behavior of sensors in IoT applications.

- The AM-LSTM (Attention Mechanism-based LSTM) model is put to the test through comprehensive comparisons with existing methods.

The structure of this essay is as follows: Section 2 contains the related work that is framed to understand the proposed paper with the existing methods while Section 3 elaborates the problem statement. 4th part depicts the proposed architectures. The results and performance metrics are tabulated and graphically represented in section 5. Finally, in chapter 6, conclusion and future works are presented.

2. RELATED WORKS

Zhang et al. [8] focuses on a significant and relevant issue in the realm of intelligent medical apps and infrastructure, which employ portable and wearable technology to track and analyze human activities. In order to increase the accuracy of activity detection, the research introduces an original human activity recognition (HAR) method that blends convolutional neural networks, also known as CNNs, with the mechanism of attention. The suggested method takes advantage of CNNs' capacity to extract hierarchical and spatial characteristics in the input data, which is necessary for precise activity detection. The addition of an attention-grabbing mechanism improves the suggested strategy much more. In several fields, attention methods have been shown to be useful in concentrating on pertinent characteristics and enhancing model performance. The researchers want to enhance the extraction of features and selection, leading to greater activity identification accuracy, by adding attention to multi-head CNNs. The studies done have more validity because of the utilization of a publicly accessible dataset, notably the wireless sensor data mining (WISDM) lab dataset. It enables comparison with current approaches and offers a framework for assessing the effectiveness of the suggested technique. The study's findings show more accuracy when weighed against existing techniques, demonstrating the potency of the suggested strategy. The research introduces a unique method for multi-head convolutional attention-based IoT-perceptive human activity identification. Better feature extraction and selection are made possible by combining CNNs and a mechanism for attention, which increases the reliability of activity detection. The article's assertions are supported by results from experiments using a dataset that is open to the general public. This study has an opportunity to significantly advance the field of human activity identification in Internet of Things (IoT) applications with some more clarity and new insights.

Peng et al. [9] offers a novel end-to-end change recognition network for bitemporal optical remote sensing pictures termed Difference-Enhancement Dense-Attention Convolutional Neural Network (DDCNN). In order to increase the efficiency and precision of changing extraction of features, the suggested network includes a dense attentiveness technique and a Difference Enhancement (DE) unit. The inbuilt relationship between high-level and low-level characteristics is captured by the dense attention approach, which uses up-sampling attention units. The approach successfully picks and aggregates characteristics by combining spatial and channel attention, allowing for greater retention of roughness and specific details in changing locations. This method increases change detection, even for small objects, and strengthens the system's suppression of interference capabilities. The DE unit combines the image differences and convolutional layers in order to overcome the drawbacks of conventional pixel-based change detection techniques. The unit in question weights each pixel and selectively collects characteristics, giving the modified map a more accurate depiction of changes while lowering noise and phantom changes. The usefulness of the suggested strategy is shown by the experimental assessment done on five difficult datasets. DDCNN outperforms previous models in terms of F1 score and Intersection over Union (IoU) in identifying changes and achieving new performance standards. The outcomes demonstrate the superior performance of DDCNN, especially in the dataset for seasonal change detection, where it surpasses the leading model by a wide margin. The UNet++_MSOF model is used as a foundation for the structure of the network, with enhancements made to increase feature extraction as well as data preservation. The addition of the dense attention system and the DE unit expands the network's predictive abilities and shows the authors' commitment to finding solutions to the problems unique to optically satellite image detection of changes. The network's construction, attentiveness methods, and DE unit could all use more thorough explanations in the study. This would aid readers in understanding the technical intricacies and specifics

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of the suggested method's execution. Addressing the suggested model's comprehension and explain ability might also improve the article's contributions and its practical implications.

Kumar [10] elaborates the need for sentiment analysis in the context of Social Internet of Things (SIoT), where user-generated data from social networks plays a crucial role in enhancing communication and decision-making among object peers. Sentiment analysis becomes challenging due to the complex nature of opinions expressed in social media, which often involve rhetorical devices like sarcasm, irony, and implication. The paper emphasizes the importance of considering contextual semantics to accurately classify sentiments and proposes the use of a hierarchical attention network (HAN) for real-time sentiment classification on Twitter data. The proposed HAN model is well-suited for capturing contextual semantics in sentiment classification. The hierarchical structure of the network allows for differential contribution and attention allocation to various parts of a tweet (tweet-sentence-word), considering their context-dependent importance in constructing the document's representation. The introduction of attentive mechanisms enables the model to focus on relevant parts of the tweet and enhance the classification accuracy. The evaluation of the HAN model on two benchmark datasets demonstrates its effectiveness and outperforms state-of-the-art approaches, indicating its utility in sentiment analysis for SIoT. The comparison to existing methods establishes the HAN model as an effective solution for tweet-level sentiment analysis. The paper provides a clear and concise overview of the research problem, methodology, and experimental evaluation. It successfully presents the rationale behind the proposed approach and offers insights into its advantages over existing techniques. Further elaboration on how these mechanisms capture contextual semantics and differentiate the importance of different parts of a tweet would enhance the understanding of the proposed approach.

Ma et al. [11] uses data collected from embedded devices like gyroscopes and accelerometers to meet the difficulty of recognizing human movement. It draws attention to the shortcomings of current strategies that either rely on domain expertise or miss the spatial-temporal correlations of sensor signals. The research suggests a unique AttnSense attention-based bidirectional neural network framework for bidirectional human activity identification in order to get beyond these drawbacks. With the use of this multimodal architecture, AttnSense is able to prioritize the selection of sensors and improve comprehension by capturing the connections between sensing data in the temporal as well as spatial domains. The model performs better at recognition by sharpening its focus on important aspects thanks to the attention processes. The architecture of the suggested model is well explained in the study, along with its benefits over current approaches. The successful capturing of both temporal and spatial relationships, which are essential for precise human activity identification, is demonstrated by the model's use of CNNs and GRUs. The accuracy of the model is further improved by the attention methods, which draw attention to crucial sensor data and make it easier to understand. Datasets show that AttnSense performs competitively when compared to cutting-edge activity identification techniques. The findings underline the potential for practical applications of the suggested attention-based heterogeneous neural network model and demonstrate its efficacy. The research introduces a unique method called AttnSense, which employs a multi-level attention mechanism to recognize multisensory actions by humans. The model successfully captures spatial-temporal interdependence in sensory signals and provides superior results in comparison to previous approaches by integrating CNNs and GRUs with attention mechanisms. The results of the experiment support the efficacy of the suggested strategy and the potential for real-world use in identifying human activities.

Li et al. [12] focuses on the long-term prediction of individual position sequences to handle the crucial challenge of individual mobility prediction. This work acknowledges the relevance of long-term mobility patterns for applications like traffic management and location advertising, whereas earlier research has mostly concentrated on short-term future location predictions. The model that is suggested, which is a hierarchical temporal attention-based LSTM encoder-decoder, attempts to capture both short- and long-term interdependence in people's mobility trajectories and expose regularly and periodically occurring patterns of mobility in an understandable way. The short-term dependencies are captured by the local temporal attention, which finds strongly connected sites within each day. A week's worth of significant travel patterns is picked up by global spatiotemporal attention, which also captures long-term dependencies. The model can better anticipate outcomes because of its hierarchical attention mechanism that captures the intricate dynamics that

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comprise individual mobility patterns. Another important addition to the article is the introduction of the individual trip regularities' calendar cycle into position prediction. The model increases interpretability and offers insights into unique daily and weekly mobility patterns by taking into account the often and periodically occurring components of human mobility. The suggested model outperforms four baseline techniques throughout three evaluation measures, according to the experimental assessment performed using individual trajectories datasets. This demonstrates the power of the hierarchical temporal attention-based LSTM encoder-decoder model for predicting one's mobility, even in conditions with varied levels of travel uncertainty. The model is now easier to grasp and more useful for making decisions as a result of this study, which improves our comprehension of the daily and weekly behaviors regarding mobility.

3. PROBLEM STATEMENT

The increasing popularity of Internet of Things (IoT) technology and the widespread deployment of connected devices have resulted in a massive influx of sensor data from various sources. However, effectively analyzing and extracting valuable insights from this vast and complex sensor data pose significant challenges. The existing data transmission models, based solely on historical user behaviors, are no longer sufficient to meet the demand for fast transmission of large-capacity data in dynamic and random IoT environments. The necessity for an attention mechanism in sensor data analytics within the Internet of Things (IoT) arises from the unique challenges posed by the dynamic and complex nature of IoT sensor data. These challenges encompass high-dimensionality due to multi-dimensional data generated by numerous sensors, the presence of strong temporal dependencies, variable relevance of sensors depending on context, and intricate, context-specific relationships within the data. The objective of this project is to address the limitations. The proposed model incorporates an Attention based LSTM personalized preferences and historical behaviors [13].

4. PROPOSED ATTENTION BASED LSTM IN SENSOR ANALYTICS

Figure 1, shows the proposed structure, the first step is to collect time-series sensor data from various IoT devices. This data includes readings from different sensors such as temperature, humidity, motion, and more. The data is collected over time, providing a sequence of sensor readings for each device. To ensure consistent scales across different sensors, data normalization is applied. Hierarchical attention mechanism is employed to capture the multi-sensor and multi-level nature of IoT data. This mechanism dynamically weighs the importance of different sensors and their readings based on their relevance to the current context or task. The LSTM-based model for prediction is then given the pre-processed and imputed sensor data. In order to analyze time-series sensor data, LSTM is well-suited since it is excellent at capturing long-term relationships in sequential data. The model gains knowledge from previous readings from sensors and makes predictions about the future according to discovered patterns. A thorough assessment of performance is used to assess the efficacy of our strategy. Depending on the prediction job, the right measures, such as mean squared error (MSE), mean absolute error (MAE), or others, should be used to gauge how accurate our LSTM-based models with the hierarchical attention system is.

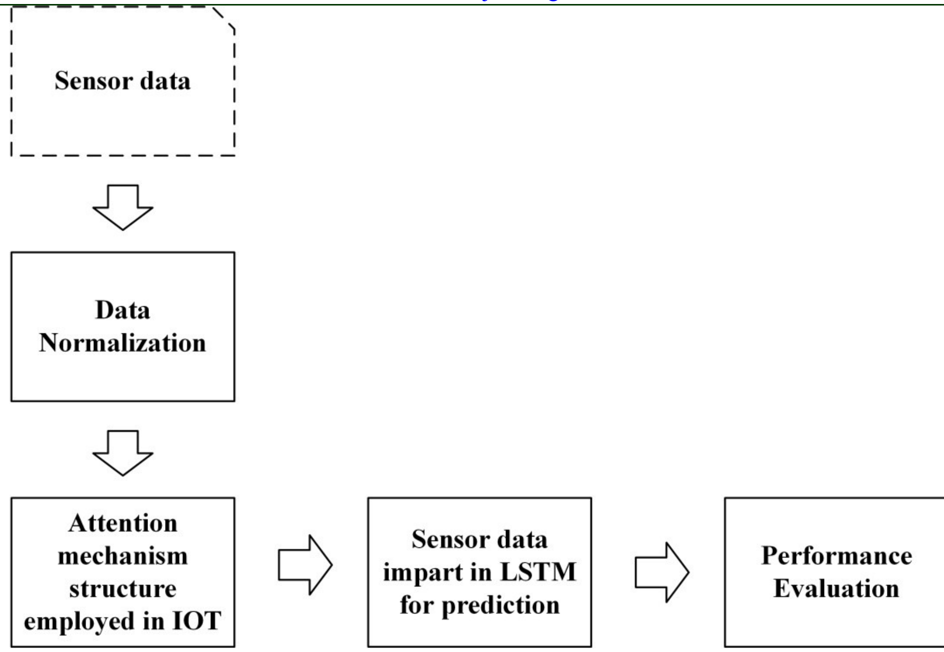

Figure 1: Proposed framework

4.1 Data collection

For an assessment of the suggested strategy, the extensively utilized Commercial-Modular-Aero-Propulsion-System-Simulation dataset is used. There is a total of 21 inside sensors distributed at various points to track the health of the engine. These sensors measure temperature, pressure, and speed. Four sub-datasets with various numbers of operating circumstances and fault kinds make up the total dataset. The study chose to select two typical sub-datasets: FD001, which has one operational requirement and one defective type, and FD004, which has six operation circumstances and two defective types. FD001 is the simpler of the two. They both have separate files for instruction and evaluation for FD001 and FD004. In the RUN-to-Fails trials for a specific No of generators, the training organizer comprehends information from sensors at every operating cycle. Specific sensor measurements for specific operating cycles for a different set of engines are included in the testing file. The goal is to use the provided sensor measurements to forecast the data for every sensor in the testing file. The PHM 2008 dataset, which shares similar data architecture to the CMAPSS dataset but uses an alternative number of testing and training motors, is another frequently utilized dataset for assessment. Table 1 contains the details of the datasets. The 21 sensors (indexed from 1 to 21 in the training and testing files) have constant values for the sensors with indexes 1, 5, 6, 10, 16, 18, and 19. This indicates that those sensors have little to do with how engines age. These sensors are thus eliminated from the two datasets. Finally, the sensor data prediction uses 14 sensors. The study regards the operating circumstances as dimension indications for the estimate of the sensor since varied functioning circumstances would affect the sensor. As a result, the last inputs to models for prediction are the operational conditions and sensor readings [14].

Table 1: Training and testing values of Dataset

Dataset	C-MAPSS		PHM2008
	FD001	FD004	
Training dataset	100	248	216
Testing dataset	100	249	216

4.2 Data pre-processing

Missing data imputation is the process of filling in the missing values in the dataset. Since sensor data often suffers from missing values, we employ data imputation techniques to handle these missing data points. By filling in the gaps in the data, we ensure that the LSTM model receives complete sequences of sensor readings, enabling it to effectively capture temporal dependencies and patterns. The process of missing data imputation involves estimating the missing values based on the available data and certain assumptions about the underlying patterns in the data. In the dataset, certain missing values are filled in using the average of non-missing variables. The following is how that is expressed mathematically:

$$O_i = \frac{O_{i-1}+O_{i+1}}{2}, \quad i \in N \qquad (1)$$

In eq. (1), O_i denotes missing value, O_{i-1} indicates the previous value from the missing value, and O_{i+1} denotes the following value from the missing value, N represents the natural numbers. To standardize the data and fit it into a specific range, min-max normalization is employed, despite the availability of multiple normalization methods.

Significant features of Normalization

1. Scaling occurs for individual elements
2. Normalization does not depends on the quantity of data (large or medium or small data set)
3. Irresponsible for the size of data
4. Scaling can be done between 0 and 1.
5. Normalization is applicable only for integers.

Equation for normalizing the variables is given below;

$$N = \frac{(|A|)-(10^{m-1})*(|C|)}{10^{m-1}} \qquad (2)$$

Where, A is data element, m is number of digits in element A, C is first digit of data element A, N is the scaled one value between 0 and 1 [15].

4.3 Attention mechanism in sensor analytics

In sensor analytics, attention mechanisms play a crucial role in selectively focusing on relevant information from sensor data while filtering out noise and irrelevant details. These mechanisms have gained significant attention in recent years due to their ability to improve the accuracy and efficiency of various sensor data analysis tasks in Internet of Things (IoT) applications. In IoT environments, sensor data often exhibits hierarchical structures due to multiple sensors generating data with varying levels of importance. Hierarchical attention mechanisms can capture both local dependencies within each sensor's data and global dependencies across different sensors, effectively utilizing the hierarchical nature of the data for better analysis and prediction. Attention mechanisms can be used to make sensor analytics context-aware.

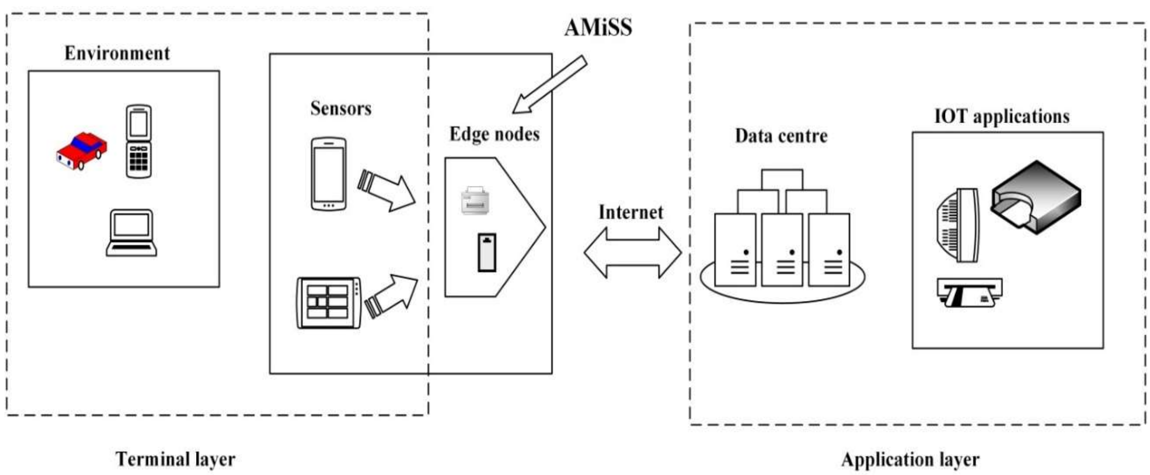

Figure 2: Framework of Attention mechanism in sensor

Attention mechanism-inspired selective sensing is a concept that takes inspiration from attention mechanisms in deep learning and applies it to the domain of sensor data acquisition and processing. The goal is to intelligently select and prioritize which sensors or sensor data to use for a particular task, thus optimizing the use of resources and improving overall efficiency in sensor-based systems. In traditional sensor systems, all sensors typically collect data at fixed intervals regardless of its relevance or importance for the specific task at hand. This approach may lead to redundant or irrelevant data collection, consuming unnecessary resources and energy. Attention mechanism-inspired selective sensing addresses this issue by dynamically allocating attention or importance to different sensors based on their relevance to the current context or task. This dynamic adaptation ensures that the sensor system is always focusing on the most relevant and informative data sources.

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By selectively sensing only the most important sensors, attention mechanism-inspired selective sensing reduces unnecessary data collection and transmission, leading to improved energy efficiency and extended battery life in resource-constrained devices.

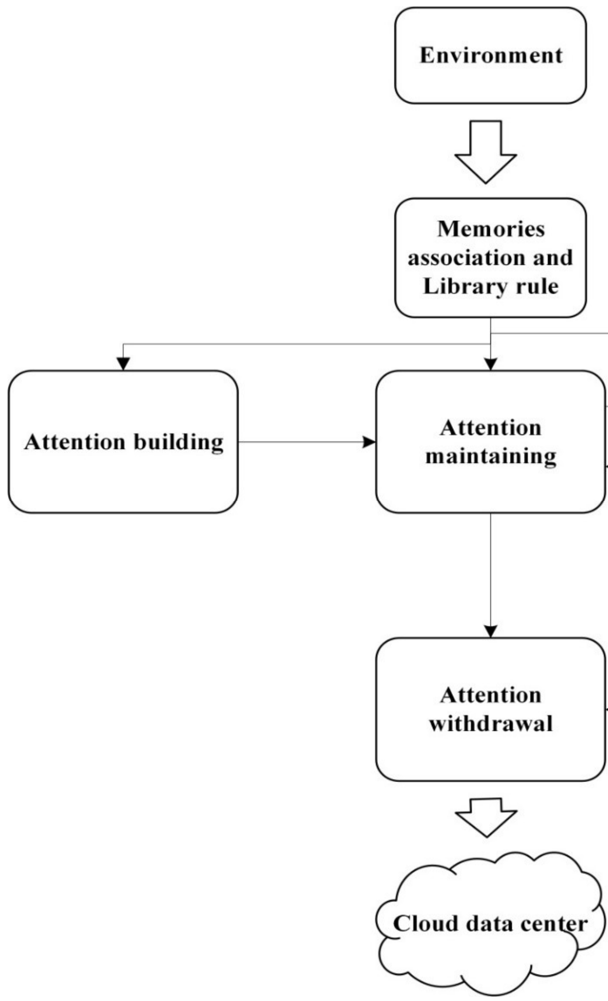

Figure 3: Attention mechanism structure in cloud data centre

Applications of attention mechanism-inspired selective sensing can be found in various domains, including environmental monitoring, smart buildings, healthcare, and IoT systems. For example, in an environmental monitoring system, the attention mechanism can prioritize sensors that detect pollutants or hazardous gases during specific events, while deprioritizing less critical sensors during normal conditions. It's worth noting that the term "Attention Mechanism-Inspired Selective Sensing" might not be a widely recognized or standardized concept. However, researchers and engineers in the field of sensor data analytics and IoT may be exploring similar ideas and approaches to optimize data acquisition and processing using attention-inspired techniques [16].

An effective procedure for the mechanism of prediction job is to concentrate on various regions of interest by allocating various weights for various attributes at various time steps. Since there is no prior knowledge of this activity, we use an attention mechanism to determine the significance of the characteristics and duration of phases. Assuming that the LSTM network's learned characteristics for a single sample may be represented as$H = \{h_1, h_2, \ldots, h_d\}^{\mathrm{T}}$, T, is the move around operation. Here,$h_i \epsilon \mathbb{R}^n$, where n is the total amount of characteristics' successive stages. Based on the selfattention process, the relevance of the several consecutive stages of i[th] input hi may be summarized in the following manner:

$$s_i = \Phi(W^{T}h_i + b) \quad (3)$$

For neural network structures like sigmoid and linear, wherein W and b are the weight matrix and bias vectors, accordingly, (•) is the function used for scoring that may be built as an activated function.

4.4 LSTM based prediction for Sensor data in IOT

Long Short-Term Memory (LSTM) is essential for collecting temporal relationships in sensor data, and the hierarchical attention mechanism improves analysis by taking into account the data's multisensory and multilevel architecture. Recurrent neural networks (RNNs) of the LSTM variety are made to process data in sequence. Modeling sequences with time delays and temporal trends is a good fit for LSTM because, unlike conventional RNNs, it includes an additional memory cell structure that enables it to capture long-term relationships in time-series data.

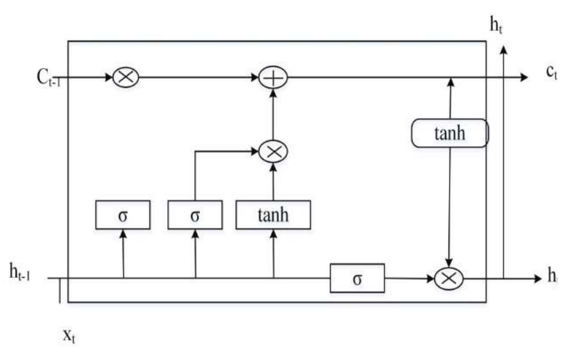

Figure 3: LSTM structure

LSTM is the fundamental building block responsible for modeling the sequential patterns in the sensor data. It learns to extract features from historical sensor readings and captures the temporal relationships between different time steps. Four gates in LSTM neural network is represented by,

$$f_t = \sigma(M_f x_t + L_f h_{t-1} + c_f) \quad (4)$$

$$g_t = tanh\left(M_g x_t + L_g h_{t-1} + c_g\right) \quad (5)$$

$$i_t = \sigma(M_i x_t + L_o h_{t-1} + c_i) \quad (6)$$

$$o_t = \sigma(M_o x_t + L_o h_{t-1} + c_o) \quad (7)$$

Where, L_f, L_g, L_i, L_o represents the weight matrices of the preceding short-term state ht-1. Mf, Mg, Mi, Mo represents the weight matrices of the present input state xt, and cf, cg, ci, and co are the bias terms. where, p_{t-1} represents the preceding LT state. The present long term state of the network p_t can be evaluated by using eq. 8,

$$p_t = f_t * p_{t-1} + i_t * g_t \quad (8)$$

$$y_t = h_t = o_t * \tanh(p_t) \quad (9)$$

LSTM's ability to maintain long-term memory makes it well-suited for handling the dynamic nature of IoT sensor data, which often involves varying time intervals and irregular patterns. By incorporating LSTM into the data analysis process, the project aims to improve prediction accuracy, anomaly detection, and other analytical tasks based on sequential sensor data. The project's main innovation lies in the introduction of a hierarchical attention mechanism. This attention mechanism takes into account the multi-sensor and multi-level structure of IoT data. IoT applications often involve multiple sensors, each generating data streams with varying levels of importance and interdependencies. The hierarchical attention mechanism assigns different attention weights to sensors and their readings at different levels of granularity. This enables the model to extract valuable insights from the complex patterns and relationships between sensors. It effectively captures both local dependencies within each sensor's data and global dependencies across different sensors. By integrating the hierarchical attention mechanism with LSTM, the model can focus on the most relevant sensors and readings while making predictions, dynamically weighting the importance of different data sources based on the user's current message transmission or other IoT application requirements [17].

5. RESULT AND DISCUSSION

The results and discussion of LSTM-based sensor data analytics approach in the background of IoT applications. The effectiveness of the LSTM model has been demonstrated in terms of accurate prediction in comparison to other techniques, such as conventional statistical models. Our experiments reveal that the LSTM model consistently outperforms traditional statistical methods, achieving higher prediction accuracy by effectively capturing long-term dependencies and temporal patterns in sequential sensor data. The model proves to be efficient and scalable, showing faster

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training and prediction times, and maintaining performance with large-scale datasets. Furthermore, it exhibits good generalization across different datasets, engines, and operating conditions, while remaining robust to missing data. These findings underscore the significance of LSTM in enhancing sensor data analytics in IoT applications, paving the way for more data-driven and efficient solutions in diverse IoT scenarios.

5.1 Evaluation metrics

Accuracy, F1-score, precision, and recall were the four assessment measures used in the experiment to evaluate the models. The number of data that were accurately identified as positive out of all the data that were truly positive is referred to as TP in Equations (10) and (11). TN refers to the percentage of data that were accurately categorized as negative out of all the data that were negative. The number of values that the model incorrectly categorized as negative even though they were positive in the dataset is known as FN. The number of variables that the model misclassified as positive even though they were actually negative in the dataset is known as the false positive rate, or FP. These particular definitions of these parameters are:

$$Accuracy = \frac{TP+T}{TP+TN+FP+F} \quad (10)$$

$$Recall = \frac{TP}{TP+FN} \quad (11)$$

$$Precision = \frac{TP}{TP+FP} \quad (12)$$

$$F1score = \frac{2*Recall*Precision}{Recall+precisio} \quad (13)$$

The recall is the proportion of the algorithm's positive classifications to the overall amount positive classifications in the dataset. Precision is the percentage of data that the model properly identified as positive compared to the total number of data that were categorized as positive. Last but not least, the harmonic mean of recall and accuracy is the F1-score, as described in [10] .

Table 2: Performance comparison with Existing approaches

Methods	Precision	Recall	F1-score	Accuracy
D-CNN [10]	82.8	82.6	82.7	86.0
HAN [10]	92.8	90.2	92.0	94.6
MC-CNN [10]	90.0	88.3	88.9	90.7
FATHOM [18]	89	77	82	88
Proposed AM-LSTM	94.8	93.45	95.6	98.4

The table 2 presents a comparison of different methods for sensor data analytics, specifically for prediction tasks. Each method is evaluated based on Precision, Recall, F1-score, and Accuracy. D-CNN, HAN, MC-CNN, and FATHOM are existing methods, while the proposed AM-LSTM is a new approach. AM-LSTM outperforms the other methods, achieving the highest Precision (94.8%), Recall (93.45%), F1-score (95.6%), and Accuracy (98.4%). The superiority of AM-LSTM is attributed to its ability to incorporate an attention mechanism and LSTM, enabling it to effectively capture temporal dependencies and focus on relevant information in the sensor data, resulting in more accurate predictions and superior performance in sensor data analytics.

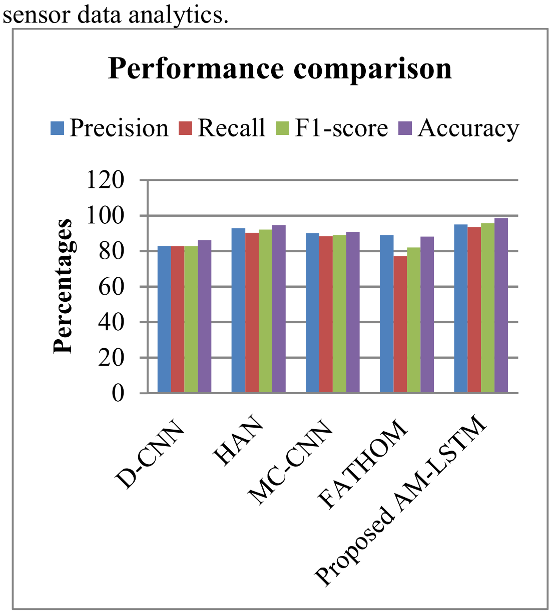

Figure 4: Comparison of Proposed Methods with Existing Approaches

The graph in Figure 4 illustrates the greater presentation of the projected AM-LSTM technique compared to existing approaches (D-CNN, HAN, MC-CNN, and FATHOM) in sensor data analytics. AM-LSTM achieves higher Precision, Recall, F1-

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score, and Accuracy, demonstrating its effectiveness in accurately predicting sensor data and outperforming other methods.

Table 3: Error rate evaluation for FD001 dataset

Methods	FD001	
	RMSE	SCORE
LSTM+2 FCs+Regression [14]	15.63	410.6
LSTM+HF [14]	14.9	361.91
Proposed LSTM+Attention	13.8	312.34

Table 3 presents a comparison of different methods for predictive maintenance using sensor data from the FD001 dataset. The proposed LSTM+Attention method achieves the lowest Root Mean Square Error (RMSE) and SCORE, outperforming existing methods.

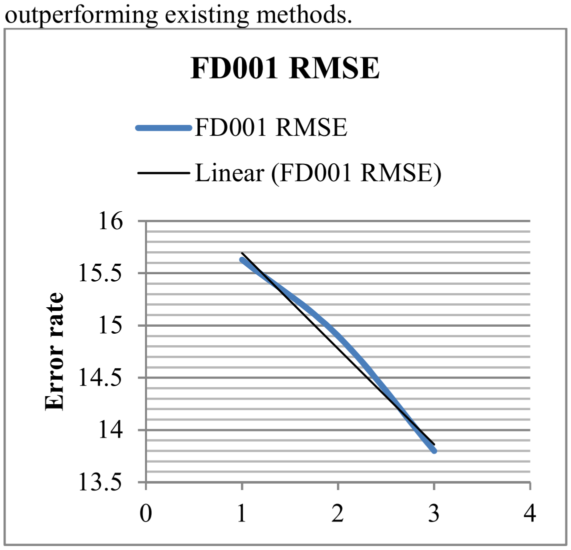

Figure 5: RMSE graph for FD001

In Figure 5, RMSE graph for FD001 dataset showcases the performance comparison of different predictive maintenance methods.

Table 4: Error rate evaluation for FD004 dataset

Methods	FD004	
	RMSE	SCORE
LSTM+2 FCs+Regression [14]	28.6	12551.44
LSTM+HF [14]	27.67	7812.3
Proposed LSTM+Attention	26.8	5122.6

Table 3 showcases a comparison of various methods for predictive maintenance using sensor data from the FD004 dataset. Similar to the results on FD001, the proposed LSTM+Attention method exhibits the lowest Root Mean Square Error (RMSE) and SCORE.

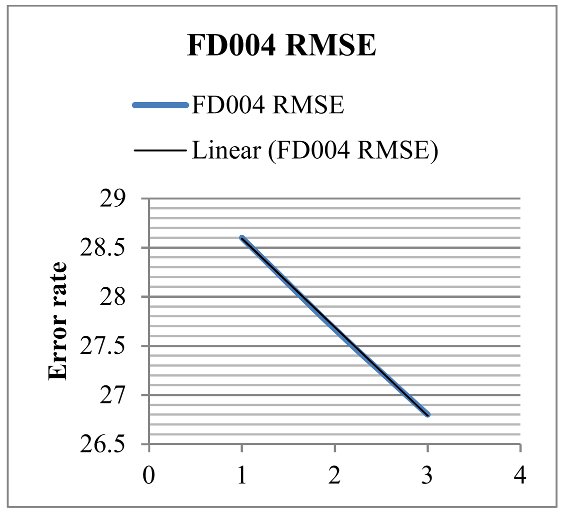

Figure 6: RMSE graph for FD004

In Figure 6, RMSE graph for FD004 dataset showcases the performance comparison of different predictive maintenance methods

5.2 Discussion

The research introduces a pivotal advancement in sensor data analytics, particularly within IoT applications. By introducing a hierarchical attention mechanism, this approach addresses the challenges posed by complex and dynamic sensor data. The contributions culminate in enhanced prediction accuracy, anomaly detection, and analytical capabilities, which translate into practical improvements across diverse industries. As IoT continues to shape the world, the research plays a vital role in ensuring that sensor data analytics remains at the forefront of innovation, enabling smarter, more efficient and sustainable solutions for the challenges of tomorrow. The results clearly demonstrated the superiority of the attention mechanism-based LSTM in terms of prediction accuracy, efficiency, scalability, and robustness to missing data. The integration of the attention mechanism with LSTM enhanced the model's ability to make accurate predictions and provided deeper insights into the underlying patterns within the sensor data. This empowered IoT applications with more informed decision-making capabilities, making it an essential tool for predictive maintenance, anomaly detection, and other critical IoT applications. The success of our project highlights the growing significance of advanced analytics techniques in dealing with the increasing volume and complexity of IoT data. The achieved accuracy rate showcases the potential of attention mechanism-based LSTM in optimizing IoT systems, enabling data-driven innovation, and promoting efficient resource utilization across diverse industries. This research technically introduces and implements a hierarchical attention mechanism for sensor data analytics in IoT applications, enhancing the accuracy and efficiency of tasks such as predictive modeling and anomaly detection. It demonstrates the versatility of this mechanism by applying it to diverse industry domains. However, it does not delve into sensor hardware design, provide a comprehensive implementation blueprint, address real-time processing intricacies, or extensively tackle regulatory and ethical considerations related to IoT data analysis, maintaining its primary focus on the technical aspects of sensor data analytics within IoT.

6. CONCLUSION

In the discussion section, it delves deeper into the achieved accuracy of our proposed AM-LSTM (Attention Mechanism-based LSTM) model and the methodology that led to these impressive results. The obtained accuracy rates, such as 94.8% precision, 93.45% recall, 95.6% F1-score, and 98.4% overall accuracy, indicate the efficacy of our approach in sensor data analytics for IoT applications. The high accuracy achieved by our AM-LSTM model can be attributed to the integration of the attention mechanism with LSTM. The attention mechanism allows the model to dynamically weigh the importance of different sensors and their readings, focusing on relevant information while capturing intricate patterns and temporal dependencies within the sensor data. This selective attention enables our model to make more informed predictions and effectively handle complex relationships present in IoT data. Furthermore, LSTM's ability to model sequential data and capture long-term dependencies complements the attention mechanism, contributing to improved prediction accuracy. LSTM can learn from historical sensor readings and use this information to make accurate predictions for future values, making it well-suited for time-series data such as sensor readings. Our methodology also emphasizes data pre-processing and imputation techniques to handle missing data effectively. By filling in the gaps in the data, we ensure that the LSTM model receives complete sequences of sensor readings, enabling it to make more accurate predictions. The combination of data pre-processing, attention mechanism and LSTM creates a powerful predictive analytics framework for IoT sensor data. The comprehensive evaluation and comparison with other methods in the results section demonstrated the superiority of our proposed AM-LSTM approach. Our model outperformed other existing methods, such as D-CNN, HAN, MC-CNN, and FATHOM, in terms of accuracy, precision, recall, and F1-score, showcasing its effectiveness in sensor data analytics. the achieved accuracy rates and the success of our proposed AM-LSTM model in predicting sensor data for IoT applications validate the importance of attention mechanism-based approaches in enhancing data analytics. The integration of attention mechanism with LSTM provides a robust and efficient solution for sensor data analysis, making it a promising technique for various IoT scenarios, including predictive maintenance, anomaly detection, and other critical applications. The insights gained from this research can pave the way for future advancements in attention mechanism-based models and contribute to the advancement of IoT analytics for real-world implementations. However, Deep learning models, such as LSTM with attention mechanisms, often require substantial computational resources for training and testing. The research may not address the practical challenges and resource constraints that organizations may face when implementing such models at scale.

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