Effective Noise Reduction using Bi-LSTM and Ethylene Detection in Bio-Nano sensors (CNT) Data

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***Abstract*—The global food supply chain faces a significant challenge with food spoilage which leads to the wastage of large quantities of perishable food items as it is difficult to handle. Spoilage happens when food deteriorates and it becomes unfit for consumption due to biological, chemical, or environmental reasons. The most important factor in spoilage is the release of ethylene gas, which accelerates ripening, and deterioration ultimately leading to the wastage of that food item. So In this article, we propose an innovative method for detecting ethylene using a carbon nanotube(CNT) based nanosensor capable of detecting trace levels of ethylene. These nanosensors sample ethylene data from multiple spatial points in real time. This sensor-collected data is transmitted through a multi-hop communication system from one node to another node. Further, this data is processed through Bi-LSTM for 50 epochs to ensure an effective noise reduction. This model achieves an RMSE (Root Mean Square Error) of 0.2621 and R^2 score of 0.1829 on our testing data highlighting its value in noise reduction in the Nano-IoT field, and also for real-world use in food monitoring and safety.**

***Index Terms*—Long Short Term Memory (LSTM), Multi-Hop Communication, xLSTM, Bi-LSTM, Carbon Nanotubes, Refined Filtering, Preliminary Filtering**

I. Introduction

The worldwide food supply system, which includes the farming, processing, and transportation of food from producers to final consumers, is crucial in meeting the daily needs of billions. So in the current food industry, packaging plays an important role in protecting the product from various Quality angles and the safety of consumers. However, the quality is affected by food spoilage resulting in the wastage of food items. Ethylene gas is the major cause of this spoilage. It increases the respiration rates leading to food softening, color change, and spoilage. Therefore, it is important to detect ethylene gas in food processing and packaging as it affects the shelf life and quality of fruits and food items. Several traditional gas detecting techniques were there but faced challenges in sensitivity and selectivity at nanoscale levels, especially in environments with diverse gas concentrations. Nowadays, nanotechnology is one of the latest technological innovations that can be used for food safety. One of the nanotechnology uses Carbon nanotube(CNT) based nanosensors which are highly effective for detecting even trace amounts of ethylene gas and help us to monitor the ripening of fruits, reduce waste, and maintain product freshness throughout the supply chain.

Previous studies about carbon nanotube(CNT) based nanosensors highlight it's unique properties to make it fit for detecting environmental and biological targets. CNTs are graphene sheets rolled in tubes and categorized into single-walled (SWCNTs) and multi-walled (MWCNTs) types. Their small size at nanoscale level provides high surface area, good conductivity, and chemical stability, which is good for biological applications. Their large surface area increases sensitivity which helps CNTs to interact with target molecules. [1]

Other research about CNT focuses on its high tensile strength, electrical conductivity, and thermal stability, which makes it highly sensitive and selective in monitoring alterations in the environment. Their large surface-to-volume ratio increases their ability to interact with target substances, allowing for accurate and quick responses, which are essential for monitoring air quality, conducting healthcare diagnostics, and maintaining security. CNTs also have good electrical properties which makes them suitable for various electrochemical and field-effect sensors. CNTs have a rapid electron transfer rate which is critical in detecting low concentrations of biomolecules such as glucose and DNA. [2] CNTs also have a flexible design that enables integration with nanoparticles that boost sensor performance and it also provides a synergistic effect that enhances both signal strength and sensitivity.

The primary objective of this research paper is to develop a reliable system using carbon nanotube (CNT) based nanosensors for detecting ethylene gas, using a multi-hop communication network to transfer data from one node to another. Further, the data processing and analysis is done using advanced machine learning techniques. This model aims to simulate ethylene adsorption on CNTs and examine how it affects the coordinates of CNTs. The focus is on the implementation and evaluation of various machine learning models including long short-term memory (LSTM), bidirectional LSTM, and xLSTM to reduce noise data transmission over the network. This study will further dive into classification models to accurately predict eyhylene presence based on denoised data and improve detection specificity.

The main contributions of this paper include:

- Collection of sample data from different spatial points of food items.
- Transmission of data from one node to another using multi hop techniques.
- Implement and compare various machine learning models (LSTM, Bi-directional LSTM, xLSTM) for denoising data transmission.
- Develop classification models to predict the presence of ethylene based on processed data.

II. Literature Review

Previous research has illustrated that carbon nanotubes (CNTs) are essential for developing unique gas sensors with nano-sized characteristics. CNTs played an important role in the development of nanosensor gas detectors that are very sensitive at detecting gasses at levels below one part per million. They also use very little power, even at room temperature. [3] The application of CNTs has been extended to sensors for the monitoring of volatile organic compounds, in healthcare and for industrial control processes. It has been shown that the CNTs have remarkable properties and are very selective to some types of gas exposure. Due to a combination of high surface area, electrical conductivity and sensitivity, CNTs are suitable materials for gas detection. [4] Because of their small curvature radius, MWCNTs or CNFs with sharp tips are used in gas sensors. The configuration establishes strong electric fields in a neighborhood of the collecting plate made of a silicon wafer coated with a thin layer of gold or stainless steel. It permits the generation of large current due to the breakdown of the gas components at lower voltages. There is a marked impact in the electrical resistance of ethylene gas molecules when they undergo attachments with CNTs hybridized with activated carbons. [5] This contact forms a dependable base for a number of activities including monitoring the disintegration of food and facilitating researches on the growth of plants.

A. Deep Learning Techniques for Noise Reduction

In recent years the advancement of nanosensor based technology comes into consideration. In exploring the effects of data transmission noise on signal detection latency. To remove the noise from the interferences has become essential from nanosensors to monitor vital parameters such as gas concentrations. In light of this type of difficulty, this challenge could be resolved with different machine learning techniques including long short-term memory (LSTM) neural networks, [6] which have proven to be useful in the task of data sequence de-noising.

Initially Support vector machines (SVM) and decision trees were considered for the analysis of nanosensor data. Moreover, the models of deep learning have the potential to identify and model complex interactions that exist over time. As for SVD based order statistics filters, we see that [7] LSTMs perform far better than other statistical filters in terms of noise suppression and enhancement of TPM reading due to its feature of gracefully predicting long range dependencies.

Long Short Term Memory networks are notable due to their effective handling of long-range dependencies, and thus find its application in complicated sequential problems. In contrast to typical neural networks, LSTMs store information across long chains, thus reducing the amount of noise in the output of nanosensors. In many situations, it is clear that LSTM-type networks are more appropriate in those applications that require quick and accurate signal detection; in particular: for gas leak detection, and for air quality assessment.

B. Multi-hop Communication in Sensor

The application of enormous frequencies in the ranges of 0.1 THz to 10 THz which are positioned between the microwave and the infrared, which support smooth transmission of data with no interruptions. THz multi-hop communication is noted to present distinct [2] challenges. On the other hand, nanosensor dimensions and their environmental adaptability require low processing and storage to avoid elaborate routing protocols. However it is significant for efficient data transfer even with THZ based multi-hop communication systems over long range transmission [8], as may be needed for monitoring agricultural fields, environmental or similar conditions. The potential of volatile gases such as ethylene gas concentrations however in multi-hop THZ networks appears to be encouraging since they support gas measurement analysis.

It has been noticed that carbon nano-sensor networks are well-suited to THz frequencies with carbon nanomaterials like carbon nanotubes (CNTs) and graphene which facilitate tasks such as molecular sensing and gas provided at necessary bandwidths[9]. However, THz frequency is also a concern for users because users are always looking for quick and consistent information through the sensing network for environmental monitoring which is closely and constantly controlled in a very short time.THz displays the high data throughput Speeds with minimal latency that is critical in real time and intensive compared with conventional frequencies.

III. Proposed Method

The proposed system architecture for ethylene detection and classification within packaged food items employs nanosensor technology, data denoising, and machine learning for accurate analysis and transmission. The architecture, as shown in Fig. 1, consists of four main stages: the Bio Nano Sensors placed on packed food items, followed by Nano Router, and then Nano Interface layer for data processing, and an IoT Gateway responsible for final classification and data transmission of data centers/etc.

A. System Architecture

The dataset used for simulating sensor behavior includes atomic coordinates of carbon nanotubes (CNTs) is taken from Kaggle Database Hub [3]. This dataset reflects structural properties that influence sensor response and assists in simulating ethylene adsorption and detection across sensor clusters.

The initial data collection occurs through Bio Nano Sensors embedded in the packed food items, such as blueberries and

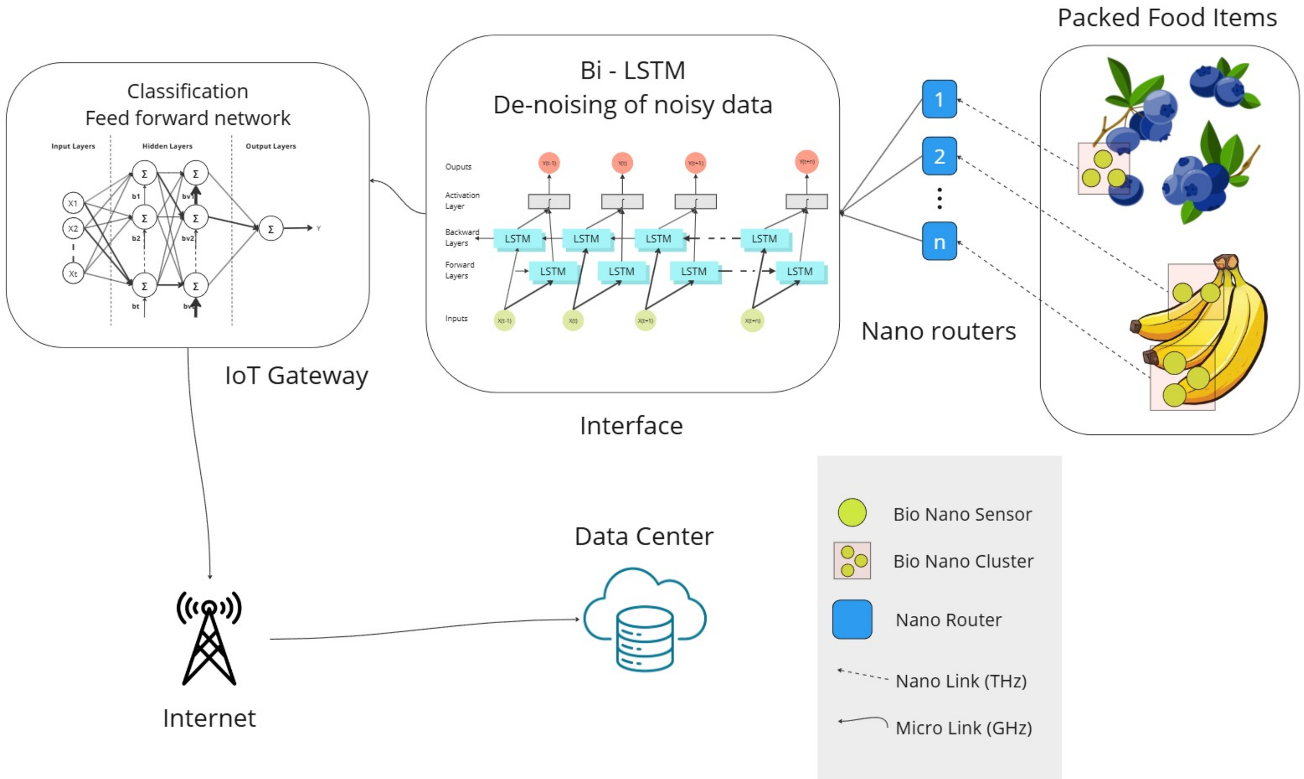

Fig. 1: IoT-based spoilage detection model for packed food, using bio-nano sensors and nano routers. A Bi-LSTM de-noises data, followed by classification at the IoT gateway and centralized analysis for spoilage prediction.

bananas. These multiple sensors when clubbed together form a clusters of sensor, which detect changes in ethylene concentration, a key indicator of ripening and spoilage in fruits. The Bio Nano Sensors transmit raw ethylene data to Nano Routers through high-frequency Nano Links using Multi-hop transmission. These Nano Routers, placed at strategic positions within the packaging, gather data from multiple sensors and forward it to the Nano Interface layer using same Nano link with the system reduces energy consumption in the nanosensors and improves overall communication efficiency.

At the Nano Interface, a Bi-LSTM (Bidirectional LSTM) model de-noises the received data. Given the small, noisy signals from nanosensors, this denoising process is crucial to ensure data accuracy before further processing. The Bi-LSTM model is optimized to handle the unique characteristics of nanoscale sensor data, capturing temporal dependencies that help filter out irrelevant fluctuations/noises while preserving the core ethylene concentration trends (relevant data).

Following de-noising, the refined data is sent to the IoT Gateway, where a feed-forward neural network performs the final classification. This model distinguishes whether the ethylene level indicates spoilage, enabling timely interventions. The IoT Gateway is also connected to the Internet, where data can be sent to a remote data center for monitoring, analysis, and storage. However, the architecture may have limitations as the dat ais processed in real-time there could be a slight delay in data transmission between the Nano Interface and the IoT Gateway due to the processing time of the Bi-LSTM model. This delay is completely depends on the model used here, in our case Bi-directional LSTM.

This comprehensive system is designed to enhance real-time spoilage detection in packed food items through precise ethylene monitoring, ultimately supporting better supply chain management and reducing food waste.

B. Bio-Nano Sensor Clustering

Bio-nano sensors are utilized in this study to identify the release of ethylene gas in packaged food products. Ethylene gas, which is naturally found in plant as a hormone, is emitted by fruits during the ripening process, and its detection can indicate the beginning of decay. In general also production Ethylene gas indicates spoilage or decay of any substance (Organic or anthropogenic sources) [4].Monitoring ethylene levels enables the detection of the starting point and location of decay, leading to proactive steps to avoid food wastage. [5]

In our architecture every yellow dot represents a bio-nano sensor with the ability to detect ethylene gas in its surrounding area. Nevertheless, the data collected by one sensor would only cover a small, specific region. Which is not enough for effective detection as the sample size is too small. To tackle this problem multiple of these bio-nano sensor are placed in a specific region which could be termed as clusters of bio-nano sensors. By Combining multiple of these clusters spread around various region can help us gain a fuller understanding of the distribution of ethylene throughout the entire food package. [6] The clusters are strategically located in various zones to establish a sensor network that gathers data from multiple areas, consequently enhancing the probability of detecting ethylene emissions from any part inside the package.

This sensor cluster configuration provides a distributed monitoring approach to reliably detect ethylene gas regardless of where it is concentrated within the food package. Because differences in fruit ripeness can result in uneven release of ethylene within the package, the use of multiple sensors allows for a more accurate understanding of overall ripeness and spoilage. [6] This design allows for the identification of specific areas where spoilage may begin, creating a detailed real-time dataset of ethylene levels in packaged foods. Ultimately, this integrated approach improves the reliability of the monitoring process by supporting timely detection of signs of spoilage and allowing more informed decisions to be made regarding the quality and shelf life of packaged foods.

C. Multi-hop Data Transmission via Nano Routers

In this research, bio-nano sensors are employed to monitor ethylene gas emissions within packed food items. Ethylene is a critical biomarker for the ripening and spoilage processes in various fruits and vegetables. The methodological design of this study focuses on the strategic deployment of bio-nano sensors to ensure comprehensive ethylene monitoring, thereby enabling more precise detection of spoilage regions within food packages.

Bio- Nano Sensor Design and Functionality

Each bio-nano sensor is engineered with high sensitivity and specificity to detect trace levels of ethylene gas. These sensors, visualized as yellow dots in our study's schematics, consist of a nanostructured material layer functionalized with ethylene-sensitive molecules [7]. When ethylene molecules come into contact with the sensor surface, they trigger a detectable response, typically a change in electrical or optical signal, which is then transmitted to a data acquisition system. This design allows for real-time ethylene detection at the molecular level, facilitating rapid and accurate assessments of fruit ripeness and spoilage.

Sensor Placement and Clustering Strategy

To ensure thorough spatial coverage of ethylene emissions throughout each food package, multiple bio-nano sensors are grouped into clusters and strategically distributed in different regions within the packed items. The clustering of sensors within the package is central to capturing a representative dataset, as ethylene emissions may vary in concentration and origin within the product due to non-uniform ripening or localized spoilage. Each cluster is positioned to cover distinct areas of the food item, forming a sensor grid that enables both regional monitoring and detection of ethylene "hotspots." These hotspots typically correspond to specific areas where microbial activity or enzymatic reactions lead to elevated ethylene release, signaling the early stages of degradation. This "hotspots" may vary based on organic substance in our case general purpose fruits, such as banana or blueberry. Specifically for banana this place is tip of fruit. But placing clusters in strategic locations, such as the top, middle, and bottom layers of the packed food items, the methodology accounts for potential variations in gas concentration due to packaging orientation, temperature gradients, and physical proximity to ripening fruits.

Spatial Coverage and Redundancy

The distributed approach with multiple clusters provides enhanced spatial coverage and redundancy. By ensuring that each part of the package is monitored by at least one sensor cluster, the likelihood of undetected ethylene emissions is minimized. This redundancy is especially critical in larger food packages where uneven distribution of ripening agents may result in isolated spoilage zones. Additionally, redundancy within clusters allows for error correction and data validation, as signals from multiple sensors within a single cluster can be cross-referenced to confirm ethylene presence.

Data Collection and Signal Processing

Each sensor within the cluster continuously transmits data on ethylene concentration levels to a central data processing unit which is called nano router. These nano routers aggregates the signals from all cluster sensors, providing a comprehensive dataset that represents the ethylene distribution within the entire package. Advanced signal processing techniques, including data filtering and noise reduction, are applied to enhance the accuracy and reliability of ethylene measurements. By analyzing variations in signal intensity and frequency, it becomes possible to identify specific areas within the package where ethylene concentrations are highest, pinpointing the initial regions of spoilage.

D. Noise Reduction Technique

Due to the sensitivity of these bio-nano sensors and environmental factors such as temperature fluctuations, humidity, and minor signal interferences, the collected raw data can contain significant noise. So, in the data collection process, the ethylene concentration data at nano-routers are further transmitted in real-time to an interface layer, where initial data processing and noise reduction take place. Noise reduction at the interface layer is, therefore, a critical step in ensuring that the ethylene concentration readings accurately reflect the actual conditions within the packed food items. To address this, three advanced de-noising methods which are —Bi-directional Long Short-Term Memory (Bi-LSTM), Long Short-Term Memory (LSTM), and Extended Long Short-Term Memory (XLSTM)—are tested to identify the most efficient approach for noise filtering and signal clarity enhancement [8].

Data Compression ("Squeezing") Before De-Noising

Before the de-noising stage, the cleaned data is subjected to a "squeezing" or compression process, which reduces its size while preserving essential information. This compression is crucial for optimizing data storage and transmission, especially in a real-time monitoring system that handles large volumes of sensor data across multiple food packages. The squeezing process is carefully calibrated to maintain the integrity of the ethylene concentration data; the compression ratio is set to minimize data loss, ensuring that all relevant ethylene emission trends and variations are retained.

The data compression process involves the following steps:

- **Data Aggregation**: Similar data points are aggregated into compressed packets that maintain the overall trend and statistical properties of the original data, reducing redundancy without sacrificing information. This is achieved using Normalization of data through the min–max normalization [9] technique defined by the formula given in below Equation. where x' is the normalized value of data.

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

- Dimensionality Reduction: Techniques such as *principal component analysis* (PCA) may be applied to reduce the dimensionality of the data, further minimizing the data footprint while preserving essential signal characteristics.

This compressed data, now smaller in size but rich in meaningful information, is prepared for further analysis and storage. By reducing data size at the interface layer, this step not only enhances data transmission efficiency but also improves computational efficiency for downstream processing steps, such as spoilage prediction and shelf-life estimation.

Comparative Noise Filtering between different LSTM Models

Standard LSTM is a modified recurrent neural network (RNN) architecture with Memory Gate to hold and carry forward previous information with current stream of data. LSTM is widely used in time-series data processing for its ability to capture dependencies in sequential data [10]. In this context, LSTM is employed to filter noise by analyzing the temporal patterns in ethylene sensor data, identifying signal trends that represent true ethylene readings while discarding transient fluctuations that are likely to be noise. However, Standard LSTM processes data in a single direction (forward), which may limit its capacity to capture complex temporal dependencies in the data, especially when noise exhibits both forward and backward correlations in time. Additionally, although effective, Standard LSTM has relatively higher computational requirements compared to other methods, making it a less ideal choice for real-time applications in large-scale food monitoring systems. We have plotted the comparison between data scale before and after using standard LSTM in Fig 2. The background red wave graphs represent the initial data received from nano-routers, blue wave graphs represent the data after using pre-processing normalization/scaling techniques which will be discussed in further sections,and the green wave graph represents the de-noised/compressed data. This shows effective reduction in noise, as well as reduction in data packet size, as non-required amplitudes and peaks are removed.

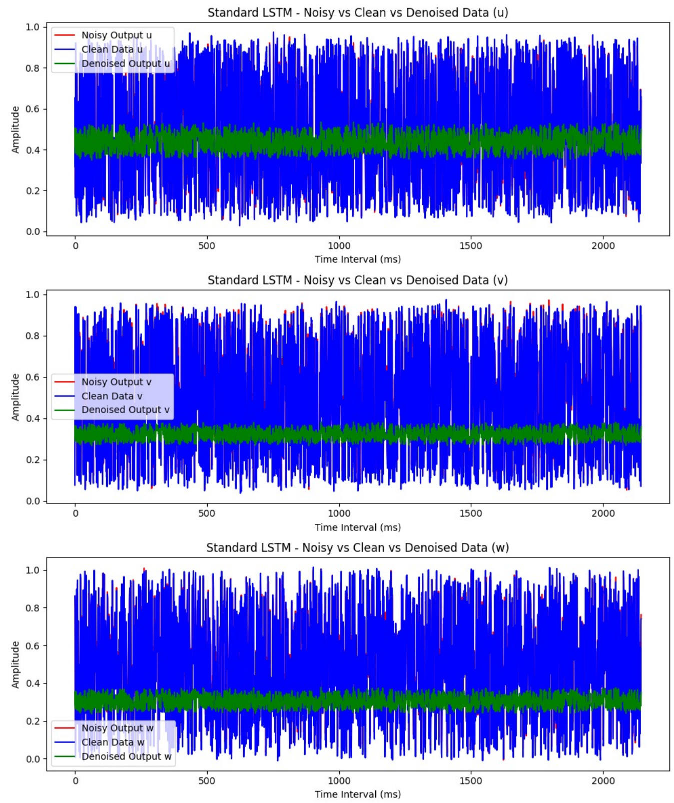

Fig. 2: Comparison collected data, cleaned data, and de-noised data using Standard LSTM Model

Extended Long Short-Term Memory (XLSTM) is an advanced modification of the LSTM architecture designed to enhance noise reduction capabilities by increasing the model's ability to retain long-term dependencies and patterns within the data [11]. This extension includes additional layers and a larger memory gate capacity, which improves the ability to process more time series data at a time enabling the filtering of complex noise signals as in Fig 3. However, due to the extended architecture, XLSTM has a high computational cost and memory requirement, making it computationally intensive. While XLSTM achieves high accuracy in noise reduction, its complexity and resource demands make it less practical for deployment in the real-time processing environment of ethylene monitoring, where efficiency is paramount.

Bi-Directional Long Short-Term Memory (Bi-LSTM), the chosen method for noise reduction, addresses the limitations of both Standard LSTM and XLSTM by processing the data in both forward and backward directions. This bi-directional approach enables the model to capture both past and future dependencies within the ethylene emission data, making it more adept at distinguishing genuine signals from noise. By taking advantage of temporal relationships in both directions, Bi-LSTM achieves a higher accuracy in noise filtering than Standard LSTM without the extensive computational load of XLSTM. Although, steps from both direction increase the computation cost but, the model was able to achieve com-

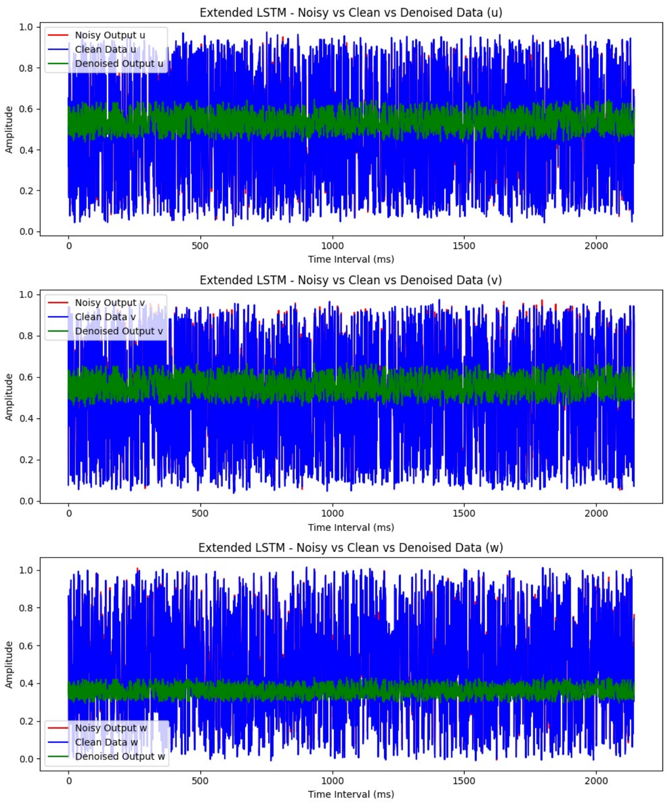

Fig. 3: Comparison between collected data, cleaned data, and de-noised data using Extended LSTM (XLSTM) Model

parative efficiency even when trained with lesser number of epochs (50 training steps). Whereas other models performance with 50 epochs was not efficient enough. This balance between performance and computational efficiency makes Bi-LSTM the optimal choice for noise reduction in this methodology that can be seen in Fig 4. After extensive testing, Bi-LSTM is selected for its superior noise reduction capabilities with minimal resource consumption, allowing for accurate, low-latency processing of the ethylene sensor data.

Noise Filtering Process Using Bi-LSTM

Upon receiving the raw data at the interface layer, Bi-LSTM is applied to each sensor cluster's readings. The Bi-LSTM model is trained to recognize patterns in ethylene concentration data that correspond to genuine signals, discarding spurious variations as noise. During this training phase, the Bi-LSTM model is exposed to both clean and noisy ethylene data samples, learning to differentiate between them based on temporal patterns. Once trained, the Bi-LSTM algorithm is able to filter noise with high precision, ensuring that the resulting data stream accurately represents ethylene concentrations in the food package.

The noise filtering process takes place in two primary stages:

- **Preliminary Filtering**: Initial data processing involves filtering out large, obvious noise spikes that are likely due to environmental factors or brief signal disturbances
- **Refined Filtering**: The Bi-LSTM model then performs refined filtering, analyzing subtler patterns and distinguishing nuanced noise artifacts from genuine ethylene signal variations [12]. This refined filtering allows for a cleaner, more accurate data stream that reflects real ethylene concentration levels, ensuring that minor but significant changes in ethylene emissions are not masked by residual noise.

The Bi-LSTM is an extension of the standard LSTM network that processes data in both forward and backward directions to capture temporal dependencies from past and future states. Here are the main equations used in an LSTM cell (unidirectional). In Bi-LSTM, we maintain two LSTMs, one for each direction, and then combine the outputs.

An LSTM cell has a memory cell c_t and three gates: the input gate i_t, forget gate f_t, and output gate o_t. [9] The updated equations are as follows:

$$\text{Forget gate:} \quad f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$\text{Input gate:} \quad i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\text{Candidate cell state:} \quad \tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

$$\text{Cell state update:} \quad c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

$$\text{Output gate:} \quad o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$\text{Hidden state:} \quad h_t = o_t \odot \tanh(c_t)$$

- W terms are weight matrices for each gate.
- b terms are biases for each gate.
- σ represents the sigmoid activation function.
- $\tanh$ represents the hyperbolic tangent activation function.
- $\odot$ denotes element-wise multiplication.

In a Bi-LSTM, we use both a forward LSTM (as defined above) and a backward LSTM that processes the sequence in reverse. The final output at each time step t is obtained by concatenating the forward and backward hidden states:

$$\text{Bi-LSTM output at time } t = \text{concatenate}(h_t^{\text{forward}}, h_t^{\text{backward}})$$

E. Detection Using Feed forward Neural Network at the IoT Gateway

After the raw ethylene data has undergone noise reduction and data compression at the interface layer, the cleaned and compressed data stream is transmitted to an IoT Gateway [13].

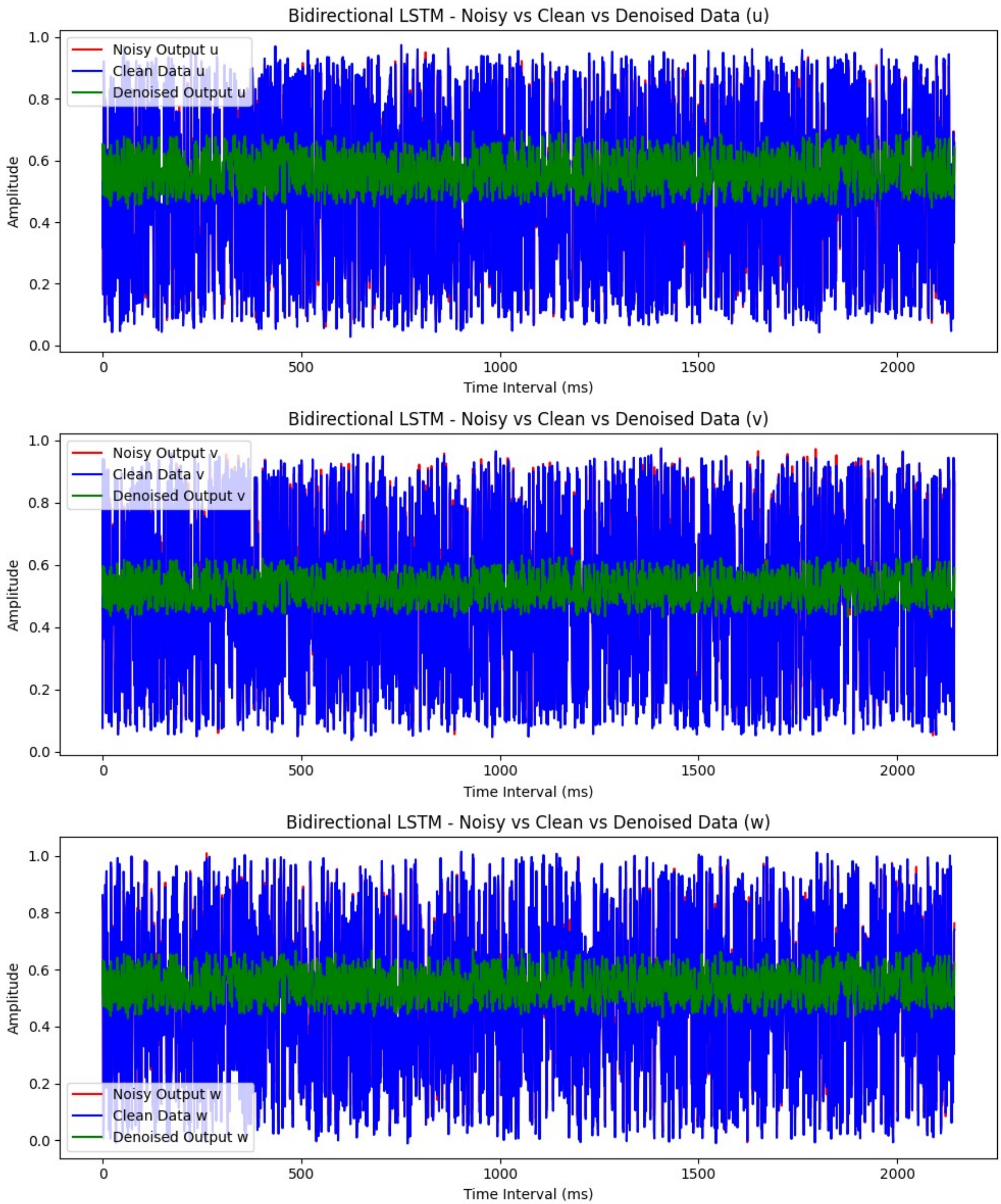

Fig. 4: Comparison between collected data, cleaned data, and de-noised data using Bi-directional LSTM Model

This gateway serves as a central processing hub, managing the real-time data flow from multiple sensor-equipped packages and facilitating advanced analysis of ethylene concentration levels. At this stage, the processed data is fed into a feed forward neural network (FNN) classifier to identify and classify instances of ethylene gas presence, which serves as a predictive marker for fruit ripening and potential spoilage [13]. The primary purpose of the FNN classifier is to distinguish data segments indicative of ethylene emissions, thereby signaling stages of food freshness and enabling timely quality control interventions.

The feed forward neural network (FNN) implemented at the IoT Gateway is designed as a multi-layer perceptron (MLP), comprising an input layer, one or more hidden layers, and an output layer [13]. Each layer consists of interconnected nodes or neurons that process incoming data by applying activation functions, allowing the network to identify patterns and trends within the ethylene concentration data.

Data Classification Process

The feed forward neural network classifier at the IoT Gateway receives a continuous, unlabeled data stream, meaning it has no prior indication of whether ethylene is present in each segment of the input data. The FNN classifier continuously evaluates the incoming data stream, identifying segments with ethylene gas and classifying them accordingly. The classification process operates as follows:

Data Ingestion: As new data arrives from the interface layer, it is batch-processed through the input layer of the FNN. Each batch corresponds to a specific time interval or cluster within the food package, allowing the model to classify ethylene emissions in a temporally and spatially localized manner.

Feature Extraction and Transformation: In the hidden layers, the data undergoes a transformation process, where weights are applied to each feature (e.g., ethylene concentration level, trend patterns) to generate a set of intermediate feature representations. These representations are passed through activation functions, such as ReLU or sigmoid, to introduce non-linearities, enabling the network to capture complex relationships between features. This stage allows the FNN to recognize patterns associated with ethylene release, distinguishing them from random fluctuations in the data.

Binary Classification: The transformed data reaches the output layer, where the FNN classifier generates a binary prediction for each data segment: presence or absence of ethylene gas. When ethylene presence is detected, it indicates that ripening processes or potential spoilage are actively occurring in the packaged food, providing an early warning signal for quality degradation. Conversely, an absence of ethylene suggests that the food remains in a fresher state, with minimal ripening or spoilage activity.

Confidence Scoring and Decision Thresholds: To improve classification accuracy, the FNN assigns a confidence score to each prediction, which quantifies the likelihood that a given data segment contains ethylene emissions. A threshold is then applied to these confidence scores, determining whether a segment is definitively classified as ethylene-present. This threshold is calibrated based on historical ethylene emission data to minimize false positives and negatives, balancing sensitivity and specificity in the detection process.

The FNN classifier's ability to detect ethylene emissions in real-time enables timely identification of spoilage-prone regions within the packed food. As ethylene release is part of the natural ripening process, an increase in ethylene concentration within specific areas of the package serves as an early indicator of food deterioration. By continuously monitoring ethylene levels, the FNN classifier provides dynamic spoilage detection, flagging areas with elevated ethylene as "at-risk" zones. This information can then be relayed to downstream quality control systems or alert mechanisms that trigger appropriate interventions, such as adjusting storage conditions or removing affected packages from distribution.

IV. Simulation Results

The simulation process was carried out in a Python environment using Jupyter Notebook and Google Colab to leverage their computational resources, enabling us to efficiently train and evaluate multiple models on large and complex datasets. The primary goal was to use various LSTM-based configurations to de-noise noisy nanosensor data, enhancing the accuracy and reliability of ethylene gas detection a critical factor in monitoring fruit spoilage in smart packaging.

Three LSTM configurations—Standard LSTM, Bidirectional LSTM, and Extended LSTM—were implemented and evaluated for their effectiveness in de-noising. Each LSTM model was trained with a consistent configuration of 100 epochs, a hidden dimension of 50, two layers, and a learning rate of 0.001. The Bidirectional LSTM outperformed the other configurations in terms of de-noising capability, showing the lowest RMSE and highest R^2 score as shown in Table I. This model's bidirectional approach allows it to capture both past and future dependencies, making it particularly effective in handling complex, noisy datasets. The Standard LSTM and Extended LSTM configurations, while performing slightly lower than the Bidirectional LSTM, still showed significant noise-reduction capabilities and provided substantial improvements to the data quality. A secondary evaluation with 50 epochs was also conducted to examine the stability of each model over shorter training cycles. Results from this run showed minimal changes in RMSE and R^2 values, indicating that these LSTM models are robust and efficient in handling noisy data, suggesting that even with lesser computation, it can reflect similar results. Which is ideal for real-world problems.

After de-noising, the processed data was used for ethylene gas classification, an essential step in assessing fruit spoilage. For this purpose, both feed-forward neural networks and a Deep Belief Network (DBN) were employed. The feed-forward network, configured with 500 epochs and three layers (64-32-1 architecture), significantly outperformed other models, achieving an accuracy of 98.30%. This model also achieved high precision, recall, and F1 scores as visible in Table II, demonstrating its strong ability to correctly classify

Model	Configuration	RMSE Error	R^2 Score	Loss after epochs
Standard LSTM	50 epochs, 50 hidden dimension, 2 num layers, 0.001 learning rate	0.2676	0.149	0.0912
Standard LSTM	100 epochs, 50 hidden dimension, 2 num layers, 0.001 learning rate	0.2617	0.1856	0.089
Bidirectional LSTM	50 epochs, 50 hidden dimension, 2 num layers, 0.001 learning rate	0.2621	0.1829	0.097
Bidirectional LSTM	100 epochs, 50 hidden dimension, 2 num layers, 0.001 learning rate	0.2733	0.1123	0.0873
Extended LSTM	50 epochs, 50 hidden dimension, 2 num layers, 0.001 learning rate	0.275	0.0995	0.0957
Extended LSTM	100 epochs, 50 hidden dimension, 2 num layers, 0.001 learning rate	0.2773	0.0863	0.0874

TABLE I: Comparison between multiple de-noising LSTM based models with different hyper-parameters

Model	Configuration	Testing Accuracy	Precision	Recall	F1-Score
Feed-Forward Network	100 epochs, 3 layers (64-32-1)	0.8116	0.7515	0.9347	0.8331
Feed-Forward Network	500 epochs, 3 layers (64-32-1)	0.9830	0.9784	0.9879	0.9831
Deep Belief Network	1 RBM layer (256 comps), Logistic Regression (100 iterations)	0.4864	0.4947	0.4917	0.4932
Deep Belief Network	1 RBM layer (256 comps), Logistic Regression (500 iterations)	0.4861	0.4944	0.4867	0.4905

TABLE II: Comparison between FNN and DBN model with different hyper-parameters

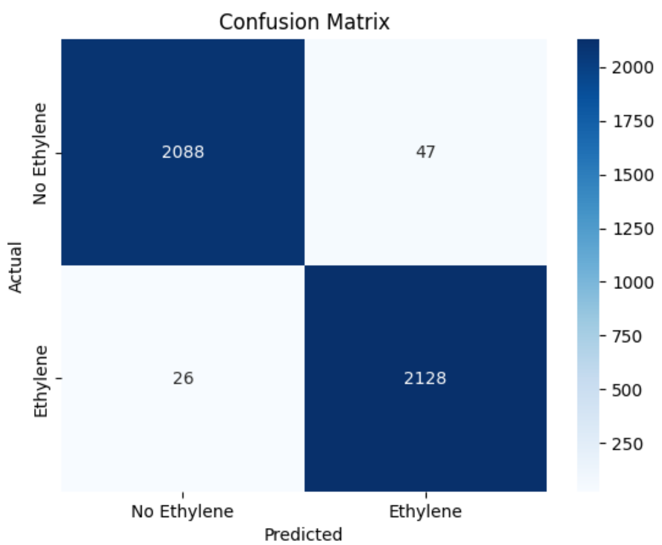

Fig. 5: Confusion matrix of Feed forward network Model

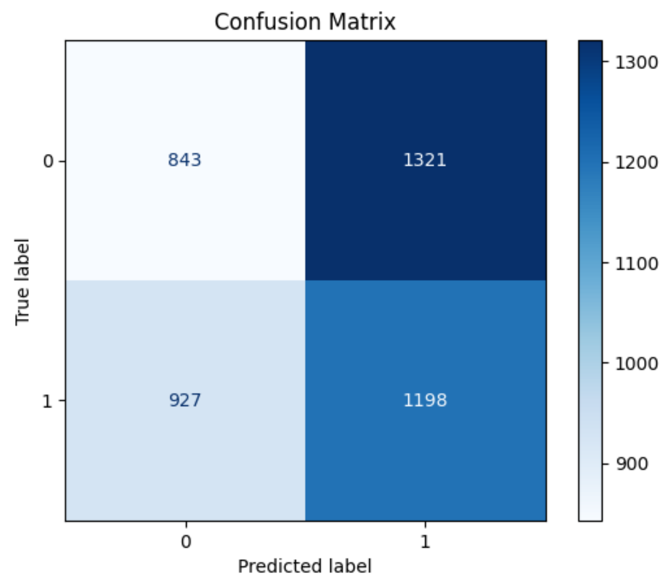

Fig. 6: Confusion Matrix of Deep Belief Network Model

ethylene presence, an indicator of fruit spoilage. The high accuracy, coupled with excellent recall and precision, suggests that the feed-forward network is highly reliable for binary classification in this context.

In contrast, the DBN struggled with accuracy, as well as with other evaluation metric. The DBN's high rate of false positives and it's true negatives limited its applicability for accurate classification, possibly due to its sensitivity to the high-dimensional, intricate patterns in nanosensor data. While the DBN maintained similarity in numbers of precision and recall is Table II, which effectively states that a balanced dataset (which should have given better results), the overall performance, efficient, and usability was incomparable to the feed-forward network.

V. Conclusion

In this study, we demonstrated the effectiveness of LSTM-based models for reducing noise in nanosensor data, followed by high-accuracy classification for ethylene detection. Our results highlight that the Bidirectional LSTM model provided the highest de-noising efficiency, with lesser number of training epochs (indicating quicker convergence towards global minimum) significantly enhancing data quality and allowing the feed-forward neural network classifier to achieve an impressive 98.30% accuracy in detecting ethylene. This pipeline, includes inital standard scaling of data using Min-Max Scaler (Could be Standard Scaler also), combining LSTM-based de-noising with feed-forward classification, establishes a promising framework for real-time ethylene detection in smart food packaging, supporting enhanced quality control and reduced spoilage rates in the supply chain.

The comparison shown in Tabel III, that our models outperform existing ones in prediction and classification tasks. Our Bi-LSTM achieved a lower RMSE (0.2621 vs. 0.4606), and our feed forward network improved accuracy (98.30% vs.

Authors	Research	Model Used	Metrics
Mo Yang, Jing Wang [2002]	Adaptability of Financial Time Series Prediction Based on Bi-LSTM	Bi-LSTM (optimized)	RMSE value of 0.46059286
	Our proposed model using Bi-LSTM	Bi-LSTM with 50 epochs and 50 hidden dimensions	RMSE value of 0.2621
Yue Huang et al. [November 2007]	Feature selection and classification model construction on type 2 diabetic patients' data	IB1 (Instance Based Learning)	Predictive accuracy of 95%
	Our Proposed model for effective classification	Multilayer Feedforward network with 100 epochs (Tri-layer network)	Predictive accuracy of 98.30%

TABLE III: Comparison of our models with models from different research

95%). These results demonstrate the robustness and effectiveness of our approaches in diverse applications.

However, the current model has certain limitations. A notable constraint is the delay introduced during data transmission between the nano interface and the IoT gateway, largely due to the sequential processing nature of the LSTM in the nano router. This added processing time can impact real-time performance, especially in high-frequency data environments. Additionally, the Deep Belief Network model encountered challenges with accuracy, particularly when dealing with high-dimensional nanosensor data, which may limit its applicability in this setup.

Future work could aim at minimizing these latency issues by optimizing the LSTM model through methods such as model pruning, quantization, or the exploration of alternative architectures like attention mechanisms. Incorporating edge computing for localized data processing could also alleviate delays by reducing dependence on the central IoT gateway. Further research into hybrid LSTM-transformer models or transfer learning could enhance noise reduction efficiency and overall processing speed, enabling more scalable and effective deployment in IoT-enabled smart packaging systems.

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