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Graphical Abstract (Optional)

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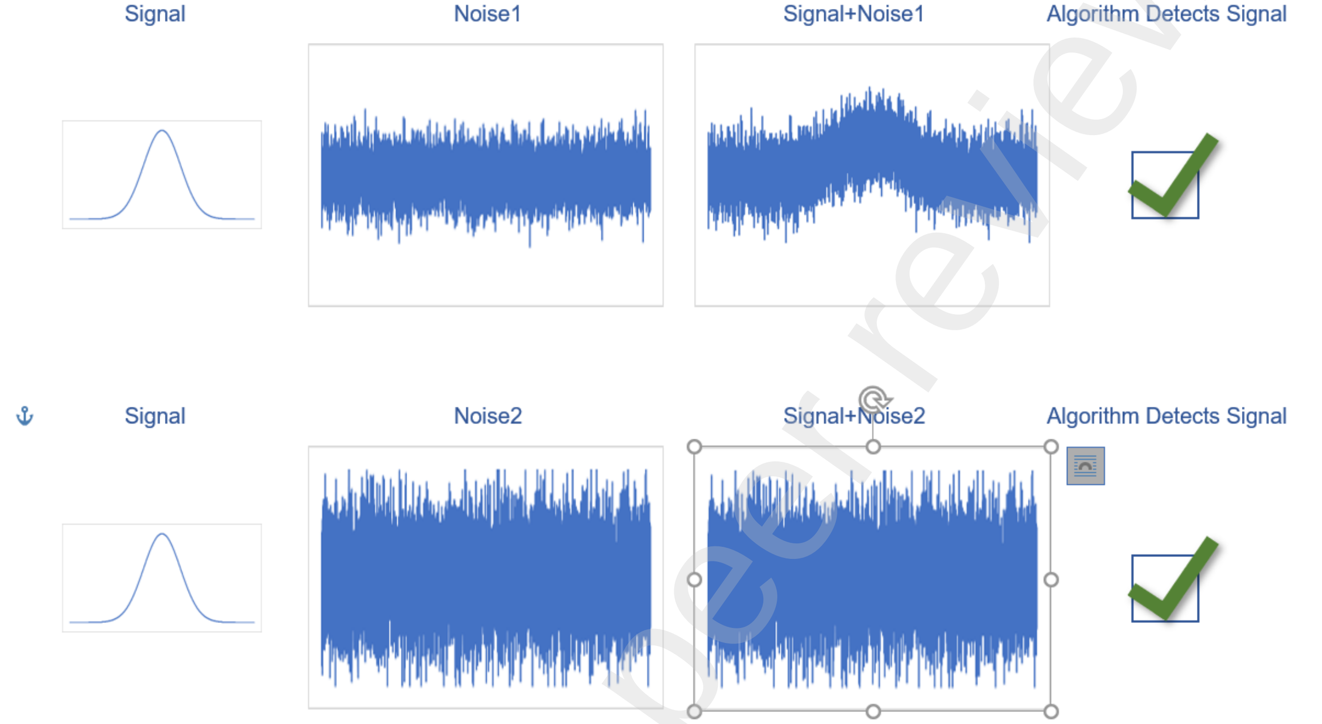

The signal in Signal+Noise1 has large SNR and is easily detectable by the ML algorithm. The signal in Signal+Noise2 has small SNR, but is also detectable by the ML algorithm.

Research Highlights (Required)

It should be short collection of bullet points that convey the core findings of the article. It should include 3 to 5 bullet points (maximum 85 characters, including spaces, per bullet point.)
Please find below an example:

- A machine learning algorithm has been developed for signal processing.
- The algorithm can detect signals with low signal-to-noise ratios (SNR).
- An accuracy greater than 98% is achieved for SNRs greater than -12 dB.
- An accuracy greater than 65% is achieved for SNRs greater than -26 dB.

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Machine Learning for Low Signal-to-Noise Ratio Detection

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ABSTRACT

Sensor networks collect data that is often contaminated by noise. Therefore, it is often necessary to analyze sensor data to determine if a signal is present. This research project utilizes a machine learning algorithm that is able to detect a signal in the presence of noise. The algorithm incorporates the long short-term memory (LSTM) method to determine the presence or absence of a signal in the midst of white Gaussian noise. This machine learning approach was tested with computer generated data and has an accuracy of at least 98% for signal-to-noise levels greater than -12 dB. Furthermore, this algorithm can detect signals at least 65% accurately for signal-to-noise levels greater than approximately -26 dB. Moreover, the presence of an anomaly in the data doesn't have a substantial impact on the detection accuracy. As a result, this detection method is very robust and has applications in surveillance and remote sensing.

Keywords: anomaly, artificial intelligence, long short-term memory, neural network, remote sensing, sensor network, surveillance

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1. Introduction

Machine learning is a branch of artificial intelligence and is described as computer programs that learn from analyzing data. Machine learning has widespread applications in many diverse fields such as agriculture, education, medicine and biology, military, computer vision, cybersecurity, and many others [1-3]. Because machine learning algorithms can be applied to a broad array of data from a variety of applications, there are unique opportunities and challenges [4]. Data that is analyzed by machine learning algorithms can be obtained from sensors [5-6]. Sensors are designed to monitor an environment and they can also provide a warning if there is a change in that environment. Incorporating machine learning techniques into sensor networks will transform conventional systems into 'smart' systems that can evaluate complex data [7].

Data collection and analysis are especially important in military as well as homeland security applications. Radar systems are used to track aerial objects and provide information about a target such as position and velocity. Military surveillance systems require additional information in order to distinguish or classify enemy targets. Additionally, military radar systems need to be very accurate and provide information in near real-time. Flight characteristics and patterns are typically used to distinguish military aircraft, but these features are not easily determined by radar operators. Unfortunately, traditional radar signal processing has some limitations in meeting these standards. Therefore, radar scientists and engineers are utilizing machine learning algorithms for prediction and classification of military targets and these algorithms are being integrated into radar systems for real-time analysis [8-9]. Moreover, technology is changing at a rapid pace, and thus emerging threats from terrorists are also rapidly advancing. To keep up with these rapid changes, detection systems must be 'smart' and adaptive. Using technology along with camera and sensor data from unmanned vehicles, preliminary patterns of terrorist activities can be monitored. Then machine learning algorithms can be used to analyze this information and thus provide warnings of terrorist attacks.

In addition to using machine learning algorithms for military procedures and operations, data analysis through machine learning has applications in military and civilian healthcare. When soldiers are on the battlefield, it is essential that they perform at peak levels. To accomplish this, body sensors can be used to measure physiological activity or performance and machine learning algorithms can process the data to predict the onset of fatigue [10-12]. Thus, soldiers can be removed from an assignment before they fall below a minimal threshold. Regarding civilian applications, machine learning has found widespread use in general healthcare and the medical field [13-14]. Prediction of cardiac arrest from electrocardiogram (ECG) signals as well as early detection of cancerous tumor cells have become extremely popular in recent years. Because the health industry generates huge amounts of clinical data, machine learning algorithms are particularly useful for detecting various features and risk factors that signal the onset of disease. Because of its predictive power and flexibility in analyzing different types of data, machine learning has become an important tool for healthcare providers.

Anomaly detection is a wide-ranging machine learning methodology that seeks to determine abnormalities or outliers amongst a group of objects or data. As a result, this data analysis technique not only has applications for military, homeland security, and healthcare purposes, but it is also useful in areas such as fraud protection and agriculture [15]. When analyzing data, an anomaly could represent unusual activity, a faulty component in a system, or the onset of a disease. Various machine learning techniques have been utilized to detect ECG abnormalities and magnetic anomalies [16-17]. Although this area of machine learning is particularly important, time series anomalies have not been studied as much as other areas [18]. Thus, extensive research is needed to determine how various machine learning algorithms can be implemented to detect anomalies in time series data.

A machine learning method known as long short-term memory (LSTM) has been the focus of several research papers and it has been successful in classifying time series data. LSTM is a recurrent neural network (RNN) and is trained or learns features from a given set of data (i.e., data from each category of interest) and then the algorithm classifies a test data set based on its characteristics. Research has shown that LSTM algorithms can accurately distinguish between different activities such as walking, sitting, and going downstairs using data from accelerometers [19-20]. Since LSTM based machine learning algorithms can properly classify different activities using time series data, it is reasonable to think it will be able to differentiate between two distinct data sets: noisy sensor data that contains a signal, and noisy sensor data that does not contain a signal.

Therefore, this research paper reports on the characteristics and ability of an LSTM machine learning algorithm to detect the presence of a signal amongst noise and how well the algorithm will perform when the signal is buried in noise (or equivalently when there is a low signal-to-noise ratio). This paper will present the methods that were used to develop the machine learning algorithm, the parameters that were used when operating the algorithm, how the data was obtained to train and test the algorithm, as well as how the signal-to-noise ratio (SNR) was calculated for this study. Finally, this report presents the results, a discussion of the results, comparisons to results of other researchers, the significance of this work, future research studies, and a conclusion.

2. Methods

2.1. Machine Learning Architecture

Researchers have developed and implemented LSTM-based machine learning algorithms using smartphone accelerometer sensor data to recognize six different human activities. These algorithms are in the public domain [21–22]. Because those LSTM algorithms are able to characterize time series data, they served as the foundation for the current research. However, the LSTM program was modified to classify and characterize signals in the presence of noise.

The code was developed using the Python programming language and the LSTM model was implemented using sklearn and keras libraries. The model is specified as a sequential model with one hidden LSTM layer with a value that was set to 128 units (this value can be modified if necessary). This LSTM layer is followed by a dropout layer (with a parameter or rate of 0.5) that helps to reduce overfitting when it is fit by the training data. This dropout layer is followed by a dense layer that was set to 64 units (the value can be modified, in parallel with the LSTM layer, if necessary). This dense layer interprets the features that are extracted by the LSTM hidden layer. This dense layer uses a rectified linear activation unit (or rectified linear unit, ReLU) which sends the appropriately weighted value to the output layer. The dense layer also uses a softmax function to scale the vector values into appropriate probability distribution values. Additionally, a binary cross entropy loss function is used to minimize the computational error of the neural network, and an adam optimizer was selected to determine the accuracy when performing the gradient descent. The learning rate was set to a value of 0.000025 (this value can be modified if necessary) and the loss rate was set to a value of 0.000015. The model was trained and tested using a batch size of 1000 samples and the number of epochs (or progressions) was set at 20 (these values can also be varied if necessary). The complete data set was divided such that 80% of the data represented the training data set (to find the parameters of the neural network) and the remaining 20% represented the test data set (to determine the accuracy of the neural network). Finally, it is noted that when the program is executed, if there is a lack of convergence or if overfitting occurs, the number of data points within a data set can be adjusted. However, if additional variations are needed, the number of epochs, the learning rate and the LSTM and dense layers can then be varied.

2.2. Computer Simulated Data (Signal and Noise)

The data presented in this paper that was used to analyze the machine learning algorithm was computer generated. The signal is generic and represents an output that a sensor would produce if it were scanning or traversing an object. This signal is similar to a Gaussian density function and it has a maximum amplitude of 1 (with arbitrary units), a standard deviation of 0.1 seconds and it exists between 0 and 1 seconds. Figure 1 displays this signal. It is noted that a true Gaussian function with a standard deviation of 0.1 seconds would have an amplitude of approximately 4. Thus, this signal represents a Gaussian function that has been scaled by 25%.

The noise is also generic and represents the random noise that would be produced by measuring the sensor output when there is no input on the sensor. The noise is represented by white Gaussian noise and has a mean of zero (i.e., centered about the origin) and the standard deviation or variance is treated as a variable so that the signal-to-noise ratio (SNR) could change during the simulations.

By adding the signal to the noise, a real-world type sensor response is obtained. Figure 2 displays graphs of noise along with the signal (from Figure 1) added to noise. The standard deviation of the noise in Figure 2 ranges from 0.2 to 10. As seen in many of the graphs in Figure 2, when the signal-to-noise ratio (SNR) is small, it is seemingly impossible to visually distinguish signal+noise from noise. However, a good machine learning algorithm will be able to accurately detect the difference between the noise and signal+noise as shown in graphs of Figure 2.

2.3. Algorithm Data Sets

In order to train and test the machine learning algorithm, two series of computer-generated data were created for each SNR. One data series contained only noise and the other data series contained the signal added to noise. Each data series contained 1-second worth of data with a total of 100 data points. A total of 10,000 different data sets were generated within the algorithm for each of two data series (i.e., signal+noise and noise only). These data series were divided to create training and testing data sets for the algorithm. Then as stated previously, 80% of the noise data sets and 80% of the signal+noise data sets were used to train the model and the other 20% was used to test the model and determine how accurate it is.

2.4. Signal-to-Noise Ratio Calculations

The area under a Gaussian function is given by $\sqrt{2\pi} * \sigma_S * A$ where σ_S is the standard deviation and A is the amplitude. Thus, the average amplitude for a Gaussian signal can be determine from $\frac{\sqrt{2\pi} * \sigma_S * A}{\Delta t}$ where Δt is the width of the signal. Thus, the average power for this signal can be determined from

$$P_S = \left[\frac{\sqrt{2\pi} * \sigma_S * A}{\Delta t}\right]^2 \quad (1)$$

Since the signal used in this study (as shown in Figure 1) has a standard deviation of 0.1 seconds, it represents a 25% scaled Gaussian since the signal height is 1 instead of 4. Thus, since the signal exists between 0 and 1 seconds, the average signal amplitude is 0.2507 and the power in the signal is $P_S = 2\pi\sigma_S^2$ or $P_S = 0.0628$. Moreover, the power of the noise is determined by

$$P_N = \sigma_N^2 \quad (2)$$

where σ_N is the standard deviation of the noise.

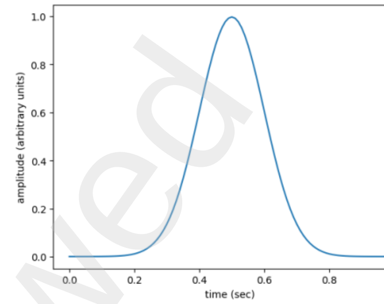
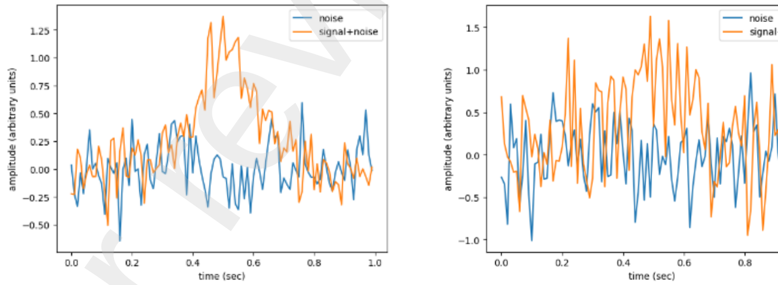
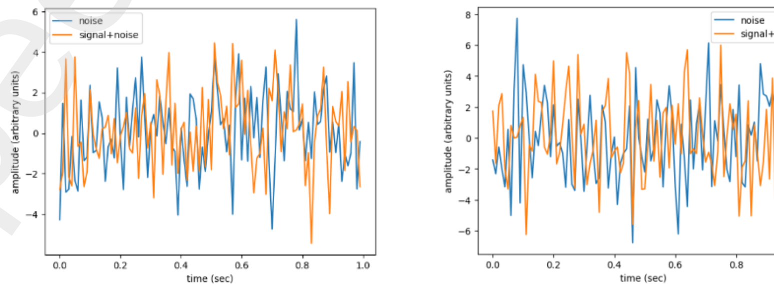


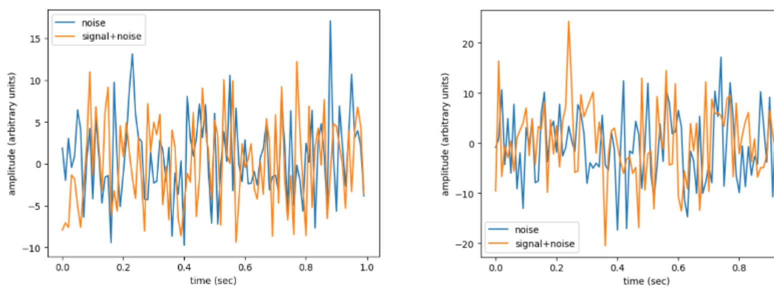
Figure 1. Computer-generated waveform that represents the 'signal' used in the analysis.



(a) (b) (c)



(d) (e) (f)



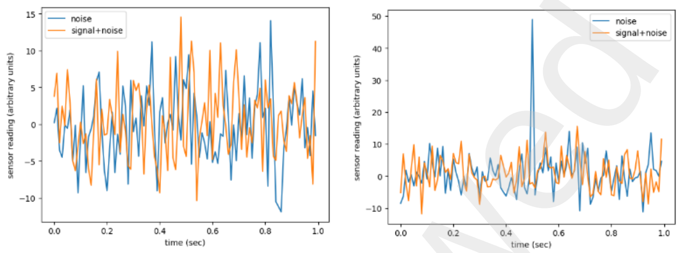
(g) (h) (i)

Figure 2. Computer-generated data (signal+noise and noise) used in the analysis with noise standard deviations of (a) 0.2, (b) 0.5, (c) 1, (d) 2, (e) 3, (f) 4, (g) 5, (h) 7, (i) 10.

In this study, the signal power is constant and the noise power is varied so that the signal-to-noise ratio (SNR) can be altered. The SNR is calculated by dividing the signal power by the noise power, and in decibels (dB) the value is equal to 10 multiplied by the logarithm of this ratio.

2.5. Anomaly Data

To further analyze the machine learning algorithm and to properly characterizing its performance, additional studies were completed to determine what affect anomalies would have on accuracy. A study was completed in which a single time point anomaly (i.e., point anomaly) was applied to the noise. The point anomaly occurred at 0.5 seconds. The value or amplitude of the anomaly varied from 0.1 to 50 (with units equivalent to noise standard deviation units). Analysis was performed for noise standard deviations of 0.5 and 5 to determine what effect (if any) the point anomaly would have on the accuracy of the algorithm at these noise levels. Graphs showing examples of these two anomalies are presented in Figure 3.



(a) (b)

Figure 3. Graph of noise and signal+noise when noise has standard deviation of 5 and contains (a) a point anomaly of value 5, (b) a point anomaly of value 50

3. Results

The machine learning algorithm was used to determine if it can distinguish the difference between a waveform that is comprised of signal+noise and a waveform that is comprised of noise alone (i.e., can the machine learning algorithm detect a signal that is buried in noise). Presumably, the accuracy of the algorithm will decrease with decreasing signal-to-noise ratios and there will be a noise level that is so large that the LSTM algorithm will not be able to detect the presence of the signal. Therefore, various signal-to-noise ratios were utilized to determine this model's level of accuracy in distinguishing these differences.

The results indicate that this LSTM-based algorithm is very successful in detecting a signal buried in noise. Table 1 shows the accuracy of the LSTM algorithm as a function of signal-to-noise ratio. The algorithm is flawless in detecting signals with SNR of -6dB and larger. As this ratio decreases, the accuracy of the algorithm also decreases. Additionally, because this evaluation is binary classification, the accuracy must be greater than 50%. It can be observed that the algorithm has a detection limit of approximately -32 dB (or the algorithm cannot detect waveforms with a signal, compared to waveforms with just noise, if the SNR is less than -32 dB).

Confusion matrices are provided in Figure 4 for each of the signal-to-noise ratios as outlined in Table 1. These matrices provide quantitative information regarding how often the machine learning algorithm successfully predicted the correct outcome given the true state of the input. So, given that the input has a signal (or does not have a signal), how often does the algorithm predict that the input contains a signal (or does not contain a signal). Thus, these matrices demonstrate the overall accuracy of the algorithm for each SNR, along with how well the algorithm specifies a signal is present when a signal is present [i.e., identifies true positives (TP)], specifies a signal is not present when a signal is not present [i.e., identifies true negatives (TN)], specifies a signal is present when a signal is not present [i.e., identifies false positives (FP)], and specifies a signal is not present when a signal is present [i.e., identifies false negatives (FN)]. Designating the quadrants of the matrix as upper left (UL), upper right (UR), lower left (LL) and lower right (LR), we have TP = [LR/(LL+LR)], TN = [UL/(UL+UR)], FP = [UR/(UL+UR)], FN = [LL/(LL+LR)].

Table 2 shows the effect that point anomalies have on the LSTM algorithm in accurately distinguishing signal+noise from noise alone. When the SNR is large (e.g., -6 dB) or equivalently when the standard deviation of the noise is small (e.g., 0.5), there is less than a 0.2 percent decrease in the detection accuracy compared to the baseline of 100%. However, when the SNR is small (e.g., -26 dB) or equivalently when the noise is large (e.g., 5), there are two different effects. There is a 3.6% maximum decrease in the detection accuracy for the point anomaly compared to the baseline of 65.35% for small anomalies, but the accuracy is driven to 100% for large anomalies. Large anomalies function like large signals and result in distinct and obvious differences that are easily detected by the LSTM algorithm.

In addition to adding a positive point anomaly of value 5 to noise, the following scenarios were also tested (at -26 dB): adding a positive point anomaly of value 5 to the signal+noise, adding a negative point anomaly of value 5 to the noise, and adding a negative point anomaly of value 5 to the signal+noise. All accuracy results were within the range of -3.6% below the baseline and +5.72% above the baseline of 65.35%. Thus, depending upon whether the anomaly is added to or subtracted from the signal or the noise, the accuracy will slightly increase or decrease from the baseline value.

4. Discussion

Because of background noise, signal detection in the midst of this noise will always be an important topic or the focus of research. Signal strength will degrade as the distance between source and receiver increases, so any improvements in signal detection will be beneficial to many scientific endeavors. Because signal detection has many different applications, the machine learning algorithm presented in this paper will have a wide variety of uses. Furthermore, because of the general approach of machine learning algorithms and the fact that they do not have to be programmed for a certain type of signal (or a certain type of noise), this type of software program can be applied to any field of research.

The result obtained for this anomaly detection machine learning algorithm seems to compare favorably with other approaches. For a SNR of approximately -7 dB, one algorithm has a 96.5% accuracy rate, while another has an accuracy rate of approximately 80% for -6 dB SNR [23-24]. In comparison, the machine learning algorithm presented in this paper provides an accuracy of 100% for an SNR of -6 dB and an accuracy of approximately 98% for an SNR of -12 dB. Additionally, these other approaches incorporate signal processing to achieve their results, whereas the LSTM method presented in this report does not require signal processing. Moreover, there is other research on signal detection that does not use pre-processed data [25]. However, in analyzing that data, a comparison demonstrates that the data and algorithm reported herein is beneficial and advantageous.

Table 1. Accuracy of the LSTM machine learning algorithm for various signal-to-noise ratios.

Standard Deviation of Noise	Signal-to-Noise Ratio	Signal-to-Noise Ratio (dB)	Classification Accuracy
0.2	1.5708	1.96 dB	100%
0.5	0.2513	-6.00 dB	100%
1	0.0628	-12.02 dB	97.97%
2	0.0157	-18.04 dB	85.10%
3	0.0070	-21.56 dB	75.15%
4	0.0039	-24.06 dB	69.38%
5	0.0025	-26.00 dB	65.35%
7	0.0013	-28.92 dB	59.30%
10	0.0006	-32.02 dB	50.15%

Table 2. Accuracy of the LSTM machine learning algorithm in detecting the signal when the noise contains an anomaly at a single time point (at 0.5 seconds).

Anomaly Value (covering 1 time point)*	Classification Accuracy when Standard Deviation of Noise is 0.5 (-6 dB)	Classification Accuracy when Standard Deviation of Noise is 5 (-26 dB)
0.1	100%	65.40%
0.2	100%	65.07%
0.5	100%	65.43%
1	100%	64.63%
2	99.95%	63.23%
5	99.85%	61.77%
10	100%	64.75%
20	100%	88.95%
50	100%	100%

*anomaly value units are the same as standard deviation

Undoubtedly, one of the significant aspects of this model is that it does not require the use of pre-processed data and thus it has the potential to be used in real-time (or near real-time). For this LSTM method, data is analyzed by the program and the algorithm provides a reasonably accurate determination about the data (i.e., whether it contains a signal or whether it is just noise). Some algorithms require pre-processed data in order to achieve high accuracy. However, in comparison, the signal-to-noise ratio does not appear to be much better for those programs and it is not clear to what extent those algorithms remain general for all types of data. Nevertheless, since sensor data can be contaminated (e.g., noise spikes, dropouts, etc.) if pre-screened or pre-processed sensor data is used for this LSTM algorithm, obviously the accuracy could be further enhanced.

When the standard deviation of the noise (or the amplitude of the noise) is at 5 or below, the algorithm has a very reasonable chance of correctly predicting the outcome. In these cases, the algorithm has minimally a 65% chance (or roughly at least 2 times out of 3) of correctly determining whether a signal exists or not. However, once the noise's standard deviation goes above 5 and approaches 10, the noise levels are so high that the algorithm cannot accurately distinguish between when a signal is actually present and when a signal is not present. Thus, the algorithm is not yet suitable or adequate when the noise is large or equivalently when signal-to-noise ratios are small. Further research and development is needed if the algorithm is needed to detect signals at these smaller SNR levels.

Regarding anomalies, if the value of an anomaly is small compared to the noise level, it is difficult (or impossible) to see the anomaly in a graph. However, if the anomaly is large compared to the noise level, it is clearly seen in the graphs of the data. In general, the results of this research demonstrate that a point anomaly doesn't significantly impact the results. If the anomaly is small, there is no impact since the accuracy results are the same as when there is no anomaly present. As the amplitude of the anomaly becomes bigger, the accuracy changes marginally from its baseline, and the signal is still easily detected by the algorithm. Finally, when the anomaly becomes very large all accuracies reach 100%. This occurs because the anomaly becomes so large that a spike in the data makes it noticeably distinguishable and thus perfectly identifiable using the algorithm. This 100% accuracy occurs regardless of the SNR level because the anomaly is being identified rather than the signal.

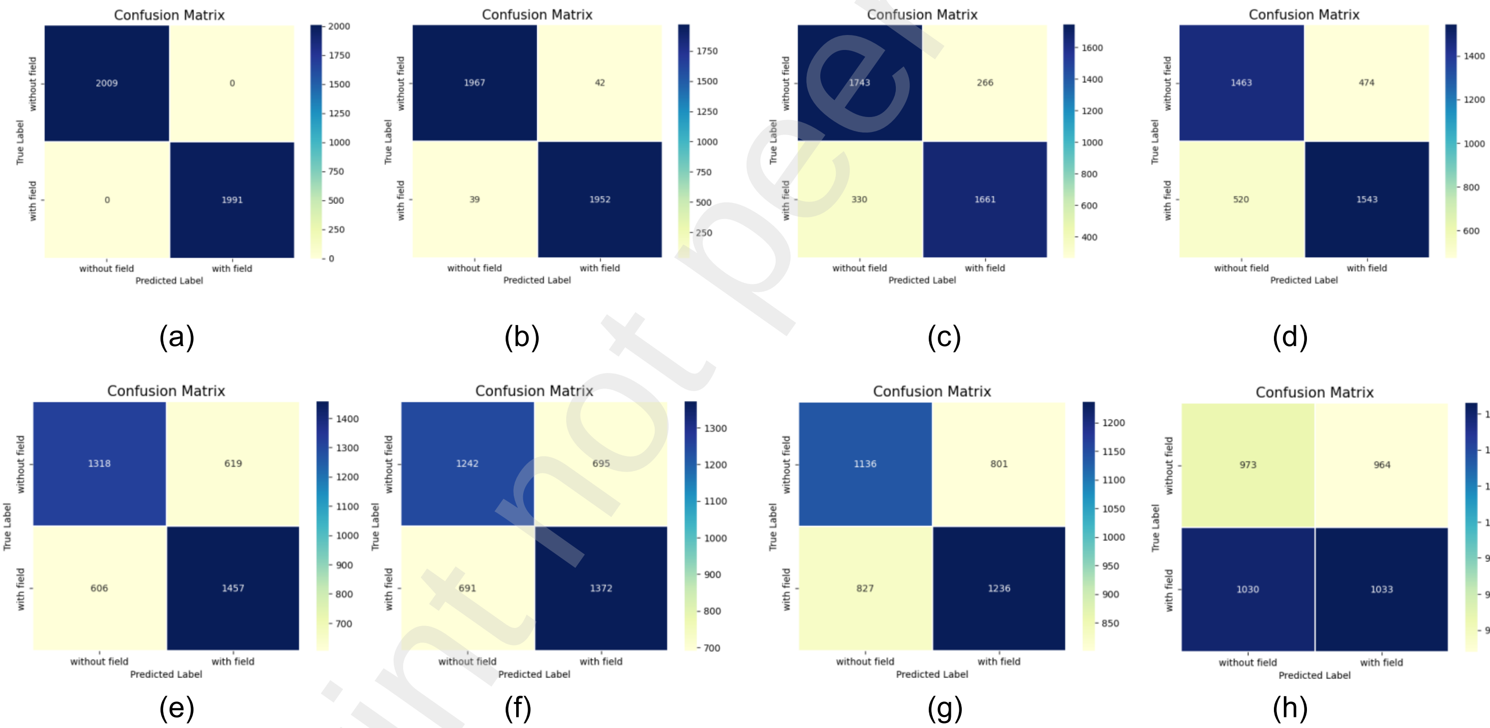


Figure 4. Confusion matrices for the LSTM machine learning algorithm for various signal-to-noise ratios (a) 1.96 dB and -6.00 dB, (b) -12.02 dB, (c) -18.04 dB, (d) -21.56 dB, (e) -24.06 dB, (f) -26.00 dB, (g) -28.92 dB, and (h) -32.02 dB.

Because anomalies are rare (and large anomalies are even rarer), these results are reasonable and demonstrate that the algorithm is robust and doesn't have any major adverse effects in detecting a signal from noise. To make the LSTM algorithm more robust, anomaly detection code could be incorporated into the algorithm to filter out and remove any outliers that are above a certain level or amplitude. This would restore all accuracy levels to their normal or baseline values (and accuracies for large anomalies would be at normal or baseline values instead of 100%).

This machine learning algorithm contains parameters that are an integral part of the success of this procedure for accurately assessing data. Parameters such as the number of layers the neural network should have, the batch size and the number of epochs, the number of units contained in the LSTM and dense layers, and the size of the learning rate and loss rate will all affect the performance of the algorithm. The relationship between these parameters and the accuracy of the algorithm's outcome is complex and further study could be performed to understand this relationship. These additional studies could enhance the performance of this algorithm. Nevertheless, the purpose of this study was to determine if the LSTM-based neural network compares favorably with other approaches to detect signals that have low signal-to-noise ratios.

Deep learning is a specific type of machine learning and is considered a subtopic within the field of artificial intelligence [26]. The primary approach to deep learning is structuring algorithms in layers so that neural networks can make more intelligent or informed decisions about the data it is analyzing. Because deep learning goes beyond machine learning, it is reasonable to believe that deep learning algorithms could provide better accuracies than a machine learning algorithm. There are several research reports that show that deep learning algorithms perform better than machine learning algorithms for various applications [27-28]. However, deep learning algorithms may require more data in order to be successful [29-30]. So, a deep learning approach could be successful in obtaining greater results for this anomaly detection type problem.

5. Conclusions

A machine learning (ML) algorithm has been developed to detect signals when background noise is present. This algorithm can detect signals in low signal-to-noise ratio (SNR) environments. The algorithm is based on the long short-term memory (LSTM) method and it has the ability to detect signals in the presence of noise if the SNR is greater than -32 dB. Moreover, if the SNR is greater than -26 dB the ML accuracy is greater than 65%, if the SNR is greater than -18 dB this ML has 85% or greater accuracy, and for SNRs greater than -12 dB the ML accuracy is above 98%. This algorithm is able to process raw data and thus does not need pre-processing to achieve this SNR. Analysis of the algorithm's accuracy when a point anomaly is present in the data demonstrates that there is no substantial effect on the results. Therefore, since data can be analyzed by the algorithm without having to be pre-processed, this algorithm is very effective in determining if a signal is buried in noise and thus has the ability to be used for real-time monitoring and surveillance.

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