Forecasting Multi-Level Deep Learning Autoencoder Architecture (MDLAA) for Parametric Prediction based on Convolutional Neural Networks

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ABSTRACT

This study presents a data-driven framework for anomaly detection, which is a significant process in modern computing, as the detection of an abnormal signal can prevent a high-risk decision. The proposed Multi-Level Deep Learning Autoencoder Architecture (MDLAA) is used to encode high dimensional input data using CNNs for anomaly detection in High Dimensional Input Datasets (HDDs). MDLAA is based on unsupervised learning, which has a strong theoretical foundation and is widely used for the detection of anomalies in HDDs, but a few limitations significantly reduce its performance. The proposed MDLAA combines multilevel convolutional layers and data preprocessing. The performance of the proposed model was evaluated on a benchmark dataset. Using feature engineering, the proposed algorithm assists in the detection of anomalies that are present in data structures, especially when compared to the ResNet101 feature extractor. The results show that given adequate data, the proposed technique outperformed other previously implemented deep learning approaches and classification models, showing an overall improvement of 2.3% in terms of MSE, F1-score, precision, and accuracy.

Keywords-Convolutional Neural Networks (CNNs); NSL-KDD; UNSW-NB15; autoencoders; anomaly detection; image classification; machine learning; data analysis

I. INTRODUCTION

Multilevel deep learning autoencoder architectures are widely used for anomaly detection in datasets, especially for ECGs and other Internet of Medical Things-based systems. These unusual irregularities, known as anomalies, can indicate important events that require immediate attention, such as extortion in financial transactions and security breaches in healthcare diagnostic frameworks. The primary objective of anomaly detection is to recognize unusual and possibly affected behavior from normal data during a predictive stage [1]. Autoencoders in cloud computing have drawbacks such as latency and lower Quality of Service (QoS) [2]. Machine learning models primarily focus on the automatic recognition of patterns to classify various issues in datasets. Multilevel deep-learning autoencoders reduce latency and improve performance by moving computational processes closer to the device, which is especially useful for time-sensitive or resource-intensive tasks in big data processing [3].

Deep learning autoencoder models based on non-intrusive methods support users to store data and perform operations remotely. The required resources are widely accessed for sophisticated operations to reduce computational burden and save time for anomaly avoidance [4]. With recent advances in time series and anomaly detection with nonlinear dimensionality processing, cloud services can detect anomalies from any location with an Internet connection. However, the use of many standards increases the complexity of maintaining a reliable system, making maintenance difficult and costly [5]. Autoencoders and parametric prediction using Convolutional Neural Networks (CNNs) can reduce QoS due to resource limitations and physical distance [6]. Figure 1 presents the schema of an ANN-based autoencoder structure that maps the input layer of the message to a code with a hidden and an output layer [7]. In [8], an unsupervised Stochastic Gradient Descent (SGD) machine learning algorithm was used to detect anomalies. In [9], an anomaly detection method was proposed for IoT transactions using CNNs to secure data, avoid anomalies, and handle complexity.

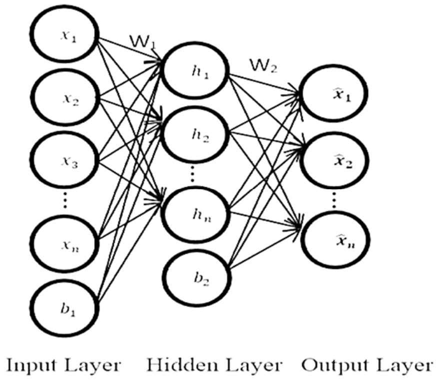

Fig. 1. Modern autoencoder structure.

II. RELATED STUDIES

In [10], a framework was proposed that used multi-layered neural networks for edge computing, describing its advantages and requirements and detailing the development of a novel server architecture for the execution of tasks in real time. This architecture aimed to meet industrial requirements and support extensibility. PCA-based real-time threat detection systems have been introduced [11, 12], using CNNs to perform parametric prediction in edge computing networks for variational autoencoders. In [13], an advanced computing node was used for anomaly detection, providing services with lower latency and bandwidth. Features including massive machine and Ultra-Reliable Low Latency Systems (URLLs) with deep learning autoencoders have been used for parametric prediction in modern computing systems, especially for High Dimensional Datasets (HDD) [14]. Big data and IoT devices based on cloud data centers are highly affected due to geographical distribution. IoT devices are widely using deep-learning-based mechanisms, specifically in large-scale data transfers, to avoid significant network congestion [15]. An edge computing-based anomaly detection method in IoT is more suitable to respond to user requests directly at the edge, leading to an innovative computing paradigm [16]. Mobile edge computing-based deep learning frameworks for anomaly detection use the Service-Oriented Computing (SOC) architecture. The fundamental idea behind edge computing is the decentralization of processing and communication resources from the cloud to the periphery of networks [17].

III. METHODOLOGY

The PTB-XL dataset [18] contains 21837 clinical ECGs with length of 10 s from 18885 patients. This dataset was used to test and validate a model based on autoencoders and a CNN in detecting anomalies. The multi-level deep learning autoencoder architecture was trained for 40 epochs. The 71 different ECG statements conform to the SCP-ECG standard and cover diagnostic, form, and rhythm statements. The CNN has three layers:

- An input layer of size |x|,
- A hidden layer of size |h| (i.e., |h|<|x|),
- An output layer of size |r| (i.e., |r|=|x|)

where size refers to the number of nodes in each layer.

A. Proposed Multi-Level Deep Learning Autoencoder Architecture (MDLAA)

An efficient CNN-based autoencoder architecture was used for the detection of anomalies, including various convolutional layers for feature extraction, pooling layers for data compression, and sampling layers for data reconstruction. The encoder compresses the input data into a lower-dimensional representation, capturing essential features while discarding noise. The decoder reconstructs the input from its representation, and the reconstruction error is used to identify anomalies.

$$ReconstructionError = \| X - \hat{X} \|^2 \quad (1)$$

where X is the original input and $\hat{X}$ is the reconstructed output.

- Input layer: The convolutional layer input is based on 32 filters, kernel size 3, and an activation function. Data are sampled at 500 Hz and 100 Hz with 16-bit resolution.
- The dense layer included 150 neurons with the ReLU activation function, conforming the output to the dimensions of the input.
- The upsampling layer upsamples the data to match the result size of the principal max-pooling layer. The effectiveness of the CNN autoencoder model is evaluated using various metrics, including accuracy, precision, recall, and F1-score.

The confusion matrix showed that the model has a high True Positive Rate (TPR) and a moderately low False Negative Rate (FNR), demonstrating compelling inconsistency recognition capacities. Its True Positives (TP) were 7604 (72.38%), indicating how many anomalies were correctly identified. The proposed model was proficient, demonstrating that it had a high TPR while maintaining a low FPR, ensuring that irregularities and issues in the data set can be easily rectified using the autoencoder. Figure 2 illustrates the proposed model. The encoder function ϕ maps the original data X to a latent space F of reduced dimensionality. On the other hand, the decoder function ψ maps (i.e., reconstructs) the latent and reduced space F to the output. In this case, the output is the same as the input data X. The encoder-decoder pair is trying to reconstruct the original data and its shape after performing and capturing a generalized nonlinear transformation.

B. Convolutional Network

The network determines the class to which an input signal belongs by determining the index of the vector's maximum value. The class represented by this index is considered as a class of the input signal. Anomalies can be detected with a high degree of accuracy by evaluating the reconstruction error. This differentiation is essential for the model's reliability in practical applications.

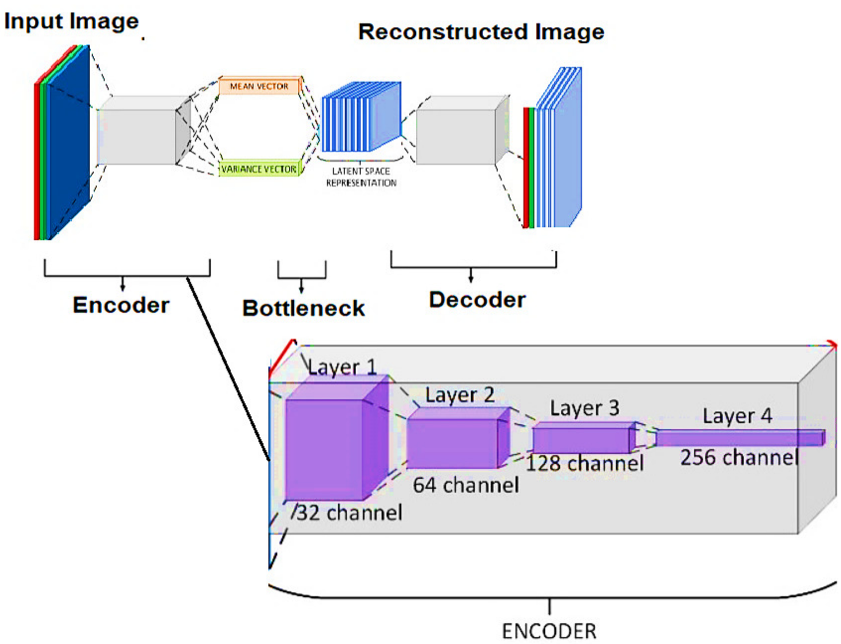

Fig. 2. Fully multilevel convolutional autoencoder for feature extraction.

TABLE I. RESULTS OF THE CNN WITH MULTIPLE CLASSES

Number of classes	Acc	Avg precision	Avg recall	Avg F1-score	Avg AUC
2	0.717	0.706	0.963	0.88	0.953
5	0.72	0.636	0.602	0.611	0.877
20	0.589	0.259	0.228	0.238	0.856

The cutoff point for identifying anomalous instances was 0.020, which is the threshold for anomaly detection. For the preparation of typical information, there is a high centralization of low recreation errors, showing that the model successfully learns and remakes ordinary examples during preparation. The TPR (affectability) against the FPR (specificity) at different limit settings could be a graphical representation of a model's symptomatic capacity. The CNN autoencoder model's capacity to recognize between typical and atypical information is illustrated by its AUC score of 0.83. The averages of accuracy and precision are per class.

The loss evaluation matrix contains the following values: True Positives (TP): 7000, False Positives (FP): 2801, True Negatives (TN): 3678, and False Negatives (FN): 277.

Accuracy incorporates all four outcomes from the confusion matrix, given a balanced dataset with similar numbers of examples in all classes.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = 0.717 \quad (2)$$

Precision is the proportion of all the model's positive classifications that are truly positive. Precision improves as false positives decrease, while recall improves when false negatives decrease. False negatives are actual positives that were misclassified as negatives. Recall measures the fraction of true positives that were correctly classified as true. Another name for recall is the probability of detection.

$$Precision = \frac{TP}{TP+FP} = 0.706 \quad (3)$$

$$Recall = \frac{TP}{TP+FN} = 0.963 \quad (4)$$

The basic convolutional network achieved better accuracy during the classification of two classes (healthy/sick). However, the results of its usage on ECG signals are far from ideal. Figure 3 shows the confusion matrix for MDLAA.

Equation (5) represents the reconstruction error as shown below. The proposed MDLAA may prove to be more advantageous compared to ResNet50 in terms of accuracy. The proposed solution could be used in small devices for continuous monitoring of ECG signals, for example, to alert about anomalies and make an initial diagnosis or support in this. Reconstruction error refers to the pixel-level reconstruction error at a specific location in a frame of a signal or video, which is calculated using a trained model. It represents the difference between the actual and the predicted intensity level by the model.

$$ReconstructionError = \| X - \hat{X} \|^2 \quad (5)$$

$$TrainingLoss = \frac{1}{N}\sum_{i=1}^{N} \|X_i - \hat{X}_i\|^2 \quad (6)$$

For a total of samples $N = 14552$:

$$TrainingLoss = \frac{1}{14552}\sum_{i=1}^{14552} (X_i - X_i')^2 \approx 0.015$$

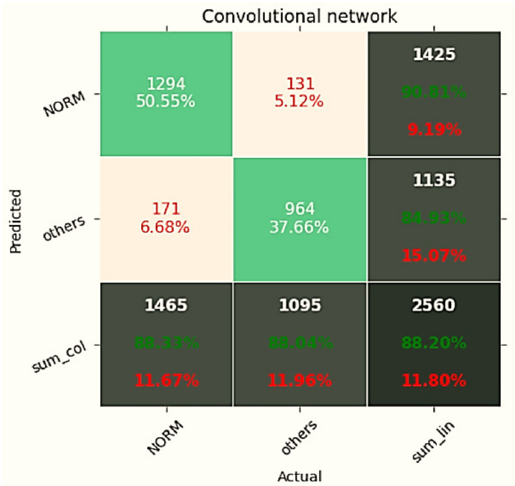

Fig. 3. Confusion matrix of MDLAA results.

Figure 4 shows the training and validation loss for the normal class and the x-axis represents the epochs ranging from 0 to 40. The reproduction errors for typical data are consistently low, indicating that the model accurately captures and imitates typical examples.

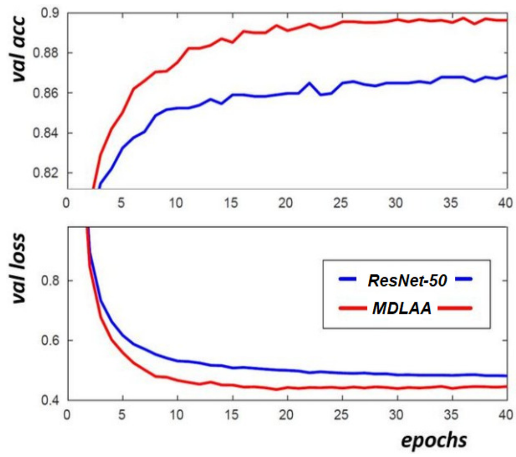

Fig. 4. Training and validation loss using the pre-trained ResNet-50 and the proposed model.

IV. CONCLUSION

This article presented a CNN-based MDLAA that was used as the top level to encode high-dimensional input data, using a CNN for anomaly detection in HDDs. The exploratory results, highlighted by measurements such as accuracy, precision, recall, F1-score, and a critical AUC of 0.83, affirm the model's capability in distinguishing anomalies with high reconstruction errors. Its capacity to capture perplexing spatial connections inside the data was confirmed on a dataset that presents real-world complexities. A multi-level deep learning approach was proposed for the direct prediction of spatio-temporal dynamics of parametric predictions. The framework was designed to address parametric and future state prediction. Future work should focus on improving the model's architecture and exploring diverse types of multilayer autoencoders based on machine learning techniques.

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