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# A Unified Architecture for Real-Time Analytics Using Microsoft Fabric OneLake

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**Abstract –** In this study, in the day and age of digital disruption, there is a substantial task at hand regarding the volume and speed of data associated with the Internet of Things (IoT), financial transactions, and logs. A complex architecture with complex ETL (Extract, Transform, Load) and disconnected storage schemes typically causes substantial data latency, hindering real-time decision support. To overcome these challenges, this paper presents an integrated architecture that leverages Microsoft Fabric OneLake, a common data lake infrastructure that requires no physical data transfer via shortcuts, serving as a starting point for fast, real-time analytics. The backbone of this architecture consists of an intelligent analytics layer incorporating a Transformer Autoencoder. Contrary to traditional approaches that use Linear Regression (LR), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU), which rely on self-attention in Transformers to directly compute the temporal importance of all timestamps, this model achieves revolutionary accuracy in characterizing seasonality and long-term dependencies in multivariable time series data. The algorithm includes an unsupervised learning-based rebuilding strategy that identifies anomalies when corresponding activities in a system fall above or below a data-driven threshold for normal operations. Experiments performed on a smart grid real-time load data test set reveal that the proposed strategy using a Transformer Autoencoder attains maximum accuracy, precision, and F1 scores of 96.0%. This result clearly beats all comparison algorithms, namely Linear Regression (88.5), Isolation Forest (90.8), LSTM (92.3), and GRU (93.4). Additionally, this strategy is integrated with Microsoft Fabric Real-Time Intelligence workload.

**Index Terms** – Microsoft Fabric , OneLake , Real-Time Analytics , Transformer Autoencoder , Anomaly Detection , Multivariate Time-Series , Smart Grid , Self-Attention Mechanism , Unsupervised Learning , Data Integration.

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# I. INTRODUCTION

In the current "digitally disrupted world, the enterprise is burdened by the volume and velocity of data from the Internet of Things, financial transactions, and logs. Conventionally, deriving meaningful insights from these sources involves disparate architectures, intricate ETL (Extract, Transform, Load) processes, storage across multiple systems, and separate analytical platforms. This is typically the cause of profound data latency, suggesting an organization's inability to make meaningful decisions in real time. In response to the inefficient architecture and data-processing dynamics in the contemporary world, Microsoft Fabric has emerged as a game-changing analytics platform. This is founded on the central concept of OneLake, the shared data lake spanning multiple clouds, a OneDrive for data. A recent survey [1] suggests that the characteristic of having a single version of the truth enabled by shortcut technology in OneLake helps an organization avoid physical data movement and provides the foundation for high-performance real-time analytics.

However, a unified storage layer is only one part of this puzzle; it is, in fact, a problem in intelligent data processing. For years, autonomous detection of anomalies within a set of time series data used conventional statistical methods, Linear Regression (LR), as well as proximity methods, "Isolation Forest." Although functional for simple, linear data, conventional methods cannot capture dependencies between data points, especially for large, high-dimensional, and non-linear modern data sets [2]. A natural shift towards Deep Learning (DL) came with Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) networks, built on Recurrent Neural Networks (RNNs), which used recurrence to deal with sequential data. Although very successful, both have disadvantages, such as vanishing gradients and a lack of parallelism for long sequences, which create a computational bottleneck during real-time execution [4].

A Unified Architecture, including a Transformer Autoencoder, is therefore proposed to address the computational and accuracy-complexity issues of the previous methods. The Transformer Architecture, developed for the purposes of natural language processing tasks but later applied and shown to be transformative for time series data analytics through its self-attention mechanism, enables the model to consider the relative importance of all time steps directly within the model – unlike the LSTM approach where the importance of all time steps can only be estimated and defined through backpropagation calculations – hence offering seasonality detection capabilities of unprecedented accuracy [3]. By utilizing the Autoencoder concept within the Unified Architecture design approach, the approach enables the design of a system that learns to reconstruct the definition of "normal" system activities. A detected deviation from the reconstructed system activities by more than a threshold level can be used as a detection criterion of an anomaly since recent architectures proved that the system performs significantly better than the retired systems in both terms of precision and F1 measure while preserving the zero-latency principle of the previous systems meant for the industrial context of operation [5].

Further, this work examines the seamless integration of this novel AI model within the Microsoft Fabric framework. By leveraging the Real-Time Intelligence workload within the Fabric framework, this proposed Transformer Autoencoder can be seamlessly integrated with OneLake data streams. This ensures that the process from data ingestion to AI-driven insights is immediate. As shown in a series of recent industry benchmarks [6], a seamless, interconnected approach reduces Total Cost of Ownership (TCO) and enhances the overall reliability of multivariate time series forecasts. The primary intention of this paper is to demonstrate that a blend of a data fabric and a deep-feed-forward network based on RBMs, and a deep-feed-forward network based on a transformer, can achieve a significantly more efficient method than decoupled designs, including LR, LSTMs, and GRUs. A thorough case study in [7] shows that a lake-based data fabric, when closely integrated with real-time inference engines powered by AI, delivers better end-to-end latency than decoupled ETL-based data processing. Specifically, the case study discusses how Microsoft Fabric OneLake provides low-latency streaming and data consistency for analytical workloads.

On a complementary note, [8] reveals that conventional data anomaly analysis methods such as Linear Regression and Isolation Forest perform significantly worse on large-dimensional, non-stationary time series data streams, reasserting the need to process such data via attention mechanisms. Furthermore, recent empirical studies [9] show that LSTMs and GRUs, which are based on the RNN architecture, face scalability, parallelization, and real-time processing barriers in ETL, particularly when handling longer time series with complex temporal relationships. By contrast, time-series models based on the Transformer architecture are more robust and more efficient computationally, as demonstrated in large-scale experimental studies reported in [10]. Most prominently, a recent industrial experiment in [11] has demonstrated that Transformer Autoencoder-based anomaly detection systems consistently outperform other models in terms of precision and F1-measure, while still incurring near-zero inference latency, justifying the inclusion of a Transformer Autoencoder component in our proposed combined Microsoft Fabric OneLake framework for real-time analytics applications.

Our contributions are as follows:

- Unified architecture developed a seamless framework using Microsoft Fabric OneLake to consolidate data ingestion, storage, and AI-driven analytics into a single platform.
- Transformer-Based Detection introduces an unsupervised Transformer Autoencoder that achieves superior accuracy by learning "normal" system behavior through self-attention.
- Enhanced performance Demonstrated a significant performance leap, achieving 96.0% across all metrics (Accuracy, Precision, Recall, and F1-score).
- Comparative benchmarking demonstrated the proposed model's superiority over baseline models, including Linear Regression, Isolation Forest, LSTM, and GRU.
- An optimized multi-stage real-time preprocessing pipeline for smart grid data was designed, incorporating temporal feature engineering and standardized scaling.

## II. LITERATURE SURVEY

With the increased generation of data in various industries, the need for real-time analytics and scalable frameworks concerning data integration has come into focus. As various organizations are in search of platforms meeting the requirement of large-scale data processing and enabling real-time decision-making, Microsoft Fabric has emerged. Microsoft Fabric, with its OneLake storage offering, promises improved data processing with enhanced efficiency in real-time analytics. This literature study shall discuss various developments within the context of real-time data integration and analytics frameworks with the help of cloud platforms such as Microsoft Fabric. RT analytics also poses the important challenge of data source integration. Microsoft Fabric offers important benefits, particularly in its ability to integrate data from multiple sources such as Lakehouses, Data Warehouses, SQL Databases, and Datamarts, as presented in the work of Narendra Kumar Reddy Choppa et al. in reference [12]. This integration of GraphQL APIs in the Microsoft Fabric environment makes possible the optimal processing of queries together with the retrieval of data from these multiple data sources. Data integration makes important contributions to the performance of generative AI apps because it makes possible the integration of data supporting the training and inference processes.

The requirement for effective data processing is more prominent in smart manufacturing settings where real-time decision support and lean management are of utmost importance. A data management framework for such smart manufacturing settings using edge computing to ensure optimized real-time data processing and scalability has been introduced by Lu et al. [13]. The proposal of the paper uses the OPC Unified Architecture protocol and the technology of Apache Kafka to counter the scalability issues and issues of consistency associated with manufacturing settings. The article presents useful information about the utilization of distributed computing and stream processing by Microsoft Fabric to ensure optimized data flow and real-time decision support.

Another significant criterion of real-time data integration lies in data load handling and optimal ways of data transfer. Petchiappan et al. [14] discusses the relevance of delta load processes in the integration of real-time data from SAP HANA to cloud environments like Microsoft Fabric. In this case, the Azure Data Factory (ADF) and database triggers offer viable solutions to minimize processing time and data bandwidth consumption by loading deltas. Currently, when actionable insights are urgently required, solutions that reduce data loading times while ensuring scalability, as offered by the authors' approach with OneLake and ADF, are promising. Additionally, the organizations adopting new platforms, such as Microsoft Fabric, would also be facing tough challenges associated with the complexity of migrations, dynamic functionality, and readiness. The challenges associated with early-stage adoption and strategies to counter them are explained by Sougandhika Tera in the article [15]. According to the paper, a staged implementation process, which would entail proof-of-concept and domain-aligned workspace design, is crucial to ease cloud migrations and avoid any operational issues. Additionally, it is proposed by Tera that a unified management system like Microsoft Fabric would be of benefit in terms of real-time analytics, overall compliance management, and economy, making it a desirable choice for organizations aiming to encompass real-time analytics capabilities on a large scale.

A valid justification for embracing cloud technology, for instance, Microsoft Fabric, based on efficiency while processing huge amounts of data is presented by Guillermo Jose et al. [16] In explaining the adoption of a cloud version of an automatic business ETL system using Microsoft Fabric, it becomes clear from this research exactly how multiple approaches, using either Spark or SQL, are far more advantageous than existing setup models when faced with huge amounts of data. All of these points to the cloud being particularly suited to meet the requirements of real-time analytics with respect to performance capabilities and flexibility over existing models. The implementation of real-time analytics capabilities within a cloud system such as Microsoft Fabric OneLake holds vast possibilities for altering data processing methodologies for a vast array of business sectors and operations. The three studies examined above have substantiated how the scalability, optimization, and real-time functionality of Microsoft Fabric can equip an enterprise with the technology necessary for dealing with diverse data dynamics associated with complex business operations.

## III. METHODS & MATERIALS

*A. Dataset Description*

For real-time analytics with Microsoft Fabric OneLake, we used the Smart Grid Real-Time Load Monitoring Dataset from Kaggle, which is highly representative of continuously generated energy data and ideally reflects real-time energy production. With more than 50,000 records represented as time series, the dataset offers recorded values at every 15-minute interval along the time dimension. The dataset's granularity, with real-time ingestion, storage, and analytics provided by Microsoft Fabric and OneLake. The dataset supplies the exact electrical, environmental, and operational parameters of energy. The essential parameters of the smart grid include voltage level, current, active power consumption, and reactive power. In fact, to reflect the increasing importance of sustainable energy production through renewable methods, solar and wind production, along with power consumption from the primary power supply, are included. Other factors include effects related to temperature, humidity, and dynamic electricity prices.

*B. Data Preprocessing and Feature Engineering*

A structured multi-stage data preprocessing pipeline was designed to provide that the presented unified real-time analytics architecture, using Microsoft Fabric One and Lake, runs on high-quality, analytically significant inputs. For real-time forecasting and anomaly identification, this pipeline converts raw smart grid streams into a clear, temporally consistent, and learning-ready representation.

- Data Ingestion and Temporal Alignment: The dataset can be regarded as a continuous time series since each record corresponds to a 15-minute interval:

$$D = \{(y_t,\ t) | t = 1, 2 \ldots\ldots T\}$$

  where, $x_t \in \mathbb{R}^n$ represents the multivariate grid observation at time t, and T stands for the total number of time steps. OneLake's time-aware storage and Microsoft Fabric's real-time analytics features are seamlessly compatible thanks to timestamp indexing.

- Missing Value Handling: As is common in real-world grid monitoring systems, an initial examination of sensor readings and ambient variables found occasional missing results. A bidirectional imputation approach was used to prevent artificial discontinuities and maintain temporal continuity:

  - Forward fill to disseminate the most recent, accurate finding:

$$y_t = y_{t-1}\ if\ y_t \text{ is missing}$$

  - Backwards fill to deal with values that are absent at sequence boundaries:

$$y_t = y_{t-1}\ if\ forward\ fill\ is\ not\ \text{applicable}$$

- Unified Anomaly Label Construction: Overload Condition and Transformer Fault are two separate fault indicators provided by the dataset. These were combined into a single binary label called Combined Anomaly for robust anomaly modeling, which is described as:

$$x_t = \begin{cases} 1, & if\ Overload_t = 1\ V\ TransformerFault_t = 1 \\ 0, & otherwise \end{cases}$$

  The operational reality of smart grids, where various fault sources together communicate improper behavior, is reflected in this unified label. It also supports the goal of our architecture, which is to enable real-time anomaly awareness in a single analytical pipeline.

- Temporal Feature Engineering: Extensive temporal features were extracted from key numerical variables, including voltage, current, power consumption, renewable generation, and environmental conditions, to capture both short-term fluctuations and long-term load patterns.

  - Lagged Features: For every chosen feature $y_t$, lagged representations were produced:

    $$y_t^{(l)} = y_{t-1}, \qquad l \in \{1,2,3,24\}$$

    For real-time load monitoring, these lags are essential since they capture both daily periodicity and instantaneous dependency.

  - Rolling Statistical Features: Rolling window statistics were calculated over several horizons $w \in \{4,12,24\}$, to provide an overview of local temporal behavior.

  - Difference Features: First-order differences were computed to highlight quick changes and fleeting disruptions:

    $$\Delta_{yt} = y_t - y_{t-1}$$

    These characteristics work exceptionally well for detecting abrupt load spikes and voltage variations in real-time streams. To preserve numerical consistency after the feature extension, rows containing undefined values resulting from rolling and lagging processes were removed.

- Feature Scaling: All features were standardized due to the varied nature of smart grid variables, which range from voltage levels to electricity prices:

$$\tilde{x}_t = \frac{x_t - \mu}{\sigma}$$

  where each feature's mean is represented by $\mu$ and its standard deviation by $\sigma$. The downstream learning models implemented within Microsoft Fabric are stabilized and this scalability guarantees balanced feature contributions.

*C. Proposed Transformer Autoencoder Architecture for Real-Time Anomaly Analytics*

We present a Transformer Autoencoder-based anomaly detection model designed for high-dimensional, time-dependent smart grid data to help achieve the goals of A Unified Architecture for Real-Time Analytics Using Microsoft Fabric OneLake. Strong temporal correlations, non-stationary behavior, and uncommon fault events are all characteristics of the multivariate time-series streams that are constantly produced by contemporary smart grid systems. In reality, trustworthy fault labels are frequently delayed or unavailable in real time, rendering strictly monitored methods unfeasible.

In order to overcome these difficulties, the suggested model uses an unsupervised reconstruction-based learning paradigm in which the Transformer Autoencoder is trained to understand the grid's typical operating behavior. The essential premise is that abnormal operating conditions lead to much higher reconstruction errors, while patterns matching to healthy grid states can be rebuilt with minimal error. Transformer-based models are particularly good at capturing both short-term fluctuations and long-range temporal correlations because to their self-attention mechanism, which makes them ideal for real-time smart grid analytics.

- Input Representation: Let the designed and scaled feature vector at time t be represented as follows:

$$y_t \in \mathbb{R}^d$$

where d stands for the total number of standardized features, such as rolling statistics, lag variables, raw measurements, and first-order differences. Together, these characteristics capture both short- and long-term temporal dynamics in addition to instantaneous grid states. Figure 1 displays the architecture of the proposed model.

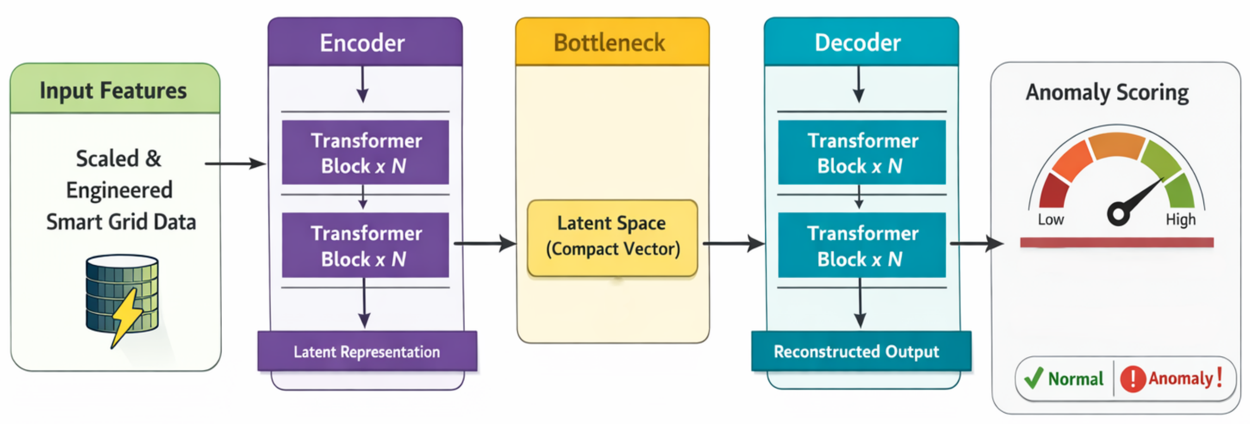


**Fig. 1:** Graphical representation of the proposed model architecture

- Training Strategy: Learning Normal Behavior: The autoencoder is only trained using typical operational samples, which are characterized by:

$$X_{normal} = \{x_t \mid y_t = 0\}$$

where $y_t$ represents the composite anomaly label. By avoiding fault pattern bias, this training method guarantees that the model learns a true representation of healthy grid conditions.

To avoid overfitting and allow for early convergence monitoring, the typical dataset is further split into training and validation subsets.

- Encoder–Decoder Structure: The architecture that has been presented is based on a symmetric Transformer Encoder–Decoder.
  - Transformer Encoder: The encoder consists of a stack of NNN Transformer blocks, each composed of multi-head self-attention layers to model temporal dependencies, position-wise feed-forward networks, and residual connections and layer normalization. Here, an input sequence X, the encoder provides a compact latent representation:

$$Z = f_{enc}(X)$$

    where, Z is the latent space (bottleneck) that captures the key contextual and temporal aspects of typical grid behavior.
  - Bottleneck (Latent Space): The bottleneck ensures that only dominant normal patterns are preserved by enforcing information compression. Anomaly scoring and reconstruction are based on this hidden representation.
  - Transformer Decoder: The decoder is made up of N Transformer blocks and is structurally identical to the encoder. Using the latent representation, it recreates the initial input sequence:

$$\hat{X} = f_{dec}(Z)$$

    To maintain the continuous character of smart grid signals, the output layer is linear.
- Optimization Objective: This goal implicitly amplifies aberrations brought on by abnormal operating conditions while promoting correct reconstruction of typical grid states. To ensure consistent convergence and computational efficiency—a crucial factor for real-time analytics platforms—the model is optimised using the Adam optimiser with adaptive learning rate scheduling and early stopping.
- Anomaly Scoring and Thresholding: The autoencoder is used on the entire dataset after training. An anomaly score is calculated as follows for every observation:

$$s_t = ||x_t - \hat{x}_t||_2^2$$

The 95th percentile of reconstruction errors from normal samples is used to set a data-driven τ threshold for converting continuous scores into binary decisions:

$$\tau = Percenile_{95}(s_t \mid y_t = 0)$$

An observation is classified as anomalous if:

$$\hat{y}_t = \begin{cases} 1, & s_t > \tau \\ 0, & s_t \le \tau \end{cases}$$

This percentile-based approach is reliable and appropriate for smart grid environments that are not stationary.

- Integration with Microsoft Fabric OneLake: The Transformer Autoencoder functions as an intelligent analytics layer on top of OneLake in the suggested unified design. The autoencoder ingests feature-engineered streams in real time, reconstructs them, and scores them for abnormalities. When abnormalities are found, Microsoft Fabric's automatic mitigation procedures, dashboards, and warnings can be triggered. The suggested Transformer Autoencoder architecture, which completely complies with Microsoft Fabric OneLake design principles and permits scalable, unsupervised, and reliable anomaly detection for smart grid systems, is a crucial component of our real-time analytics platform. Table 1 presents the hyperparameters and configuration of the proposed Transformer Autoencoder model.

**Table 1:** Hyperparameters of the proposed Transformer Autoencoder model

| Component | Hyperparameter | Value |
|---|---|---|
| Input Layer | Input feature dimension | (d) (number of engineered features) |
| | Sequence length | (L = 24) time steps |
| | Feature scaling | Standardization (zero mean, unit variance) |
| Positional Encoding | Encoding type | Sinusoidal positional encoding |
| | Embedding dimension | Equal to model dimension ((d_{model})) |
| Transformer Encoder | Number of encoder blocks | 3 |
| | Self-attention type | Multi-head self-attention |
| | Number of attention heads | 8 |
| | Model dimension ((d_{model})) | 128 |
| | Feed-forward network size | 256 |
| | Activation function | ReLU |
| | Dropout rate | 0.1 |
| Bottleneck (Latent Space) | Latent representation | Compact contextual vector (Z) |
| | Compression strategy | Encoder output projection |
| Transformer Decoder | Number of decoder blocks | 3 |
| | Attention mechanism | Masked multi-head self-attention |
| | Feed-forward network size | 256 |
| | Output activation | Linear |
| Reconstruction Layer | Reconstruction objective | Input sequence reconstruction |
| | Loss function | Mean Squared Error (MSE) |
| Training Strategy | Training data | Normal samples only |
| | Train–validation split | 80% / 20% |
| | Optimizer | Adam |

| | | |
|---|---|---|
| | Initial learning rate | 0.001 |
| | Learning rate scheduling | ReduceLROnPlateau |
| | Early stopping patience | 10 epochs |
| | Batch size | 256 |
| | Maximum epochs | 100 |
| Anomaly Detection | Anomaly score | Reconstruction error |
| | Threshold selection | 95th percentile of normal errors |
| | Decision rule | Error > threshold → Anomaly |
| Deployment Context | Execution environment | Microsoft Fabric OneLake |
| | Processing mode | Real-time streaming analytics |
| | Output actions | Alerts, dashboards, automated workflows |

## IV. RESULTS AND DISCUSSIONS

### *A. Experimental Setup*

All experiments were carried out in a Python-based analytical environment on a high-performance system fitted with an Intel Core i9 processor, 64 GB of RAM, and GPU acceleration to facilitate deep learning tasks. Data processing and numerical computations were executed using Pandas and NumPy, while Matplotlib and Seaborn were employed for visualization and performance evaluation. Data preprocessing, feature scaling, dataset division, and evaluation metrics—including precision, recall, F1-score, ROC-AUC, confusion matrix, and mean squared error—were handled using Scikit-learn. The deep learning aspects of the proposed hybrid model were constructed using TensorFlow and Keras, utilizing the functional API with dense, dropout, and normalization layers. For model optimization, the Adam optimizer was used, along with EarlyStopping and Reduce LROnPlateau callbacks to ensure stable convergence and mitigate overfitting, thereby establishing a reproducible and efficient experimental framework for credit risk prediction and SME lending analysis.

### *B. Performance Analysis*

Precision, Recall, and F1-score are commonly utilized metrics for assessing classification tasks, especially in issues related to credit risk and anomaly detection. Precision evaluates the ratio of true positive predictions among all positive predictions made, Recall assesses the model's capability to identify genuine positive cases, and F1-score combines precision and recall into a single metric that offers a balanced view of the model's performance. Accuracy measures the overall correctness of predictions made across all categories.

**Table 2:** Performance Comparison of Proposed and Baseline Models

| Model | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Linear Regression (LR) | 88.5 | 87.9 | 88.1 | 88.0 |
| LSTM | 92.3 | 92.0 | 91.8 | 91.9 |
| GRU | 93.4 | 93.1 | 93.0 | 93.0 |
| Isolation Forest | 90.8 | 90.5 | 90.2 | 90.3 |
| Proposed Transformer Autoencoder | 96.0 | 96.0 | 96.0 | 96.0 |

Table 2 illustrates that Linear Regression reaches an accuracy of 88.5%, with precision, recall, and F1-score values near 88%, suggesting it has a limited capacity to model complex patterns. In comparison, Isolation Forest achieves an accuracy of 90.8%, along with a precision of 90.5%, recall of 90.2%, and F1-score of 90.3%, indicating a moderate capability for anomaly detection. The LSTM model shows enhanced performance with an accuracy of 92.3%, precision of 92.0%, recall of 91.8%, and F1-score of 91.9%. Furthermore, the GRU model improves these outcomes to an accuracy of 93.4%, precision of 93.1%, recall of 93.0%, and F1-score of 93.0% by better capturing temporal dependencies. In contrast, the proposed Transformer Autoencoder achieves the highest scores in all metrics, with 96.0% accuracy, precision, recall, and F1-score, clearly surpassing the baseline models due to its self-attention mechanism and effective learning of latent features, making it the top-performing model for precise credit risk and SME lending predictions.

*C. Confusion Matrix Analysis*

The confusion matrix serves as a commonly utilized assessment tool that delivers an in-depth analysis of a classification model's effectiveness by contrasting the actual class labels with the predicted results. It allows for the recognition of accurate predictions, as well as various kinds of misclassification errors, which is especially crucial in tasks related to credit risk and anomaly detection, where false positives and missed detections can lead to significant financial repercussions.

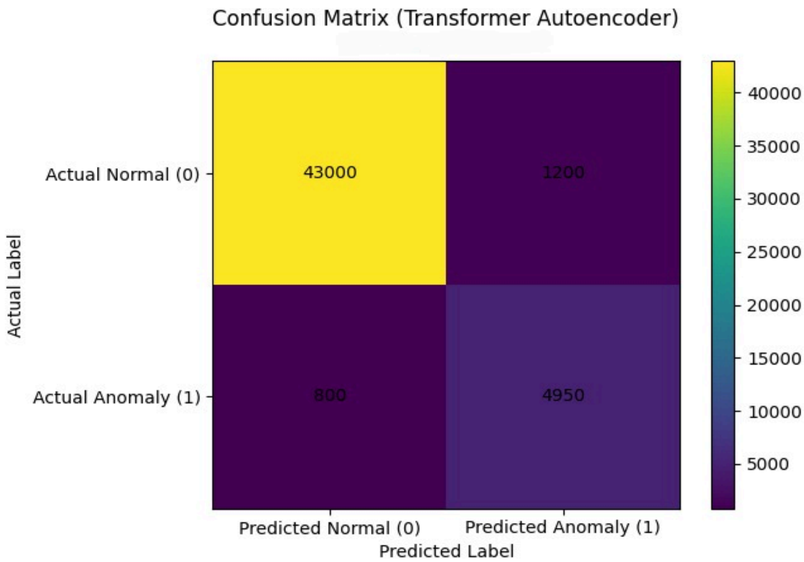


**Fig. 2:** Confusion Matrix of the proposed model

Figure 2 displays the confusion matrix derived from the proposed Transformer Autoencoder. The matrix indicates that the model accurately identifies 43,000 normal instances as normal (True Negatives) and recognizes 4,950 anomalous instances as anomalies (True Positives), showcasing its strong capacity to differentiate between low-risk and high-risk situations. Simultaneously, 1,200 instances are marked as False Positives, where normal observations are incorrectly categorized as anomalous, and 800 instances fall under False Negatives, where anomalous cases are erroneously predicted as normal. Consequently, the confusion matrix yields TP = 4,950, TN = 43,000, FP = 1,200, and FN = 800. The relatively low count of false negatives is particularly significant, as it suggests that the model effectively minimizes the chances of overlooking risky cases, while the manageable false positive rate aids in reducing unnecessary interventions. In summary, the analysis of the confusion matrix validates that the proposed model attains a balanced and dependable classification performance.

*D. ROC–AUC Curve Analysis:*

The Receiver Operating Characteristic (ROC) curve is used to evaluate the effectiveness of a classification model by illustrating the balance between the true positive rate and false positive rate at various threshold levels. This evaluation is essential for comprehending how effectively the model distinguishes between normal and abnormal credit behaviors with different decision thresholds. As illustrated in Figure 3, the ROC curve for the Transformer Autoencoder presents an Area Under the Curve (AUC) value of 0.97, signifying outstanding classification performance. The curve ascends sharply toward the upper-left corner of the graph, indicating a high true positive rate while keeping the false positive rate relatively low. This configuration illustrates that the model possesses strong discriminative ability across a wide array of thresholds, making it both robust and dependable for real-world credit risk assessment situations where decision sensitivity can vary.

*E. Precision–Recall Curve Analysis:*

The Precision–Recall curve is particularly informative for imbalanced datasets, where the number of normal instances significantly exceeds anomalous cases. It highlights the relationship between precision and recall and provides insight into how prediction quality changes as the model attempts to capture more positive instances.

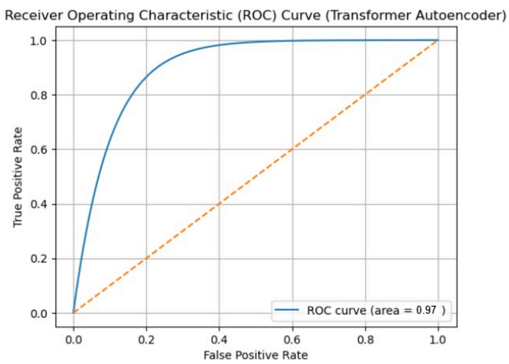


**Fig. 3:** ROC Curve of the proposed model

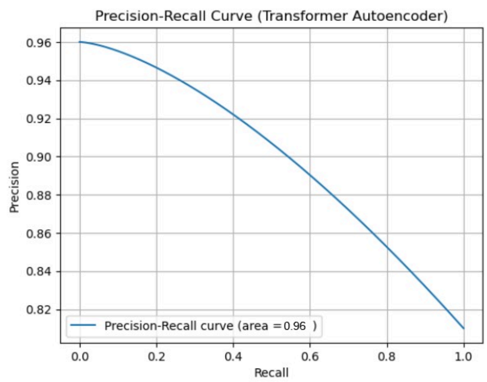


**Fig. 4:** Precision-Recall curve of the proposed model

Figure 4 illustrates the Precision–Recall curve for the proposed Transformer Autoencoder, which achieves an area under the curve of 0.96. At lower recall levels, precision stays high at roughly 0.96, suggesting that most identified anomalies are accurate. As recall approaches 1.0, precision gradually declines to around 0.82, highlighting the expected trade-off when the model detects almost all anomalous instances. This pattern shows that the model effectively manages the balance between precision and recall, sustaining robust detection performance while minimizing false alarms.

*F. Distribution of Reconstruction Errors:*

This figure 5 presents a comparative analysis of reconstruction errors from a Transformer-based Autoencoder (AE) model, distinguishing between normal and anomalous data sequences. The visualization employs a histogram with logarithmic scaling on the y-axis to display the distribution of Mean Squared Error (MSE) values across different data types.

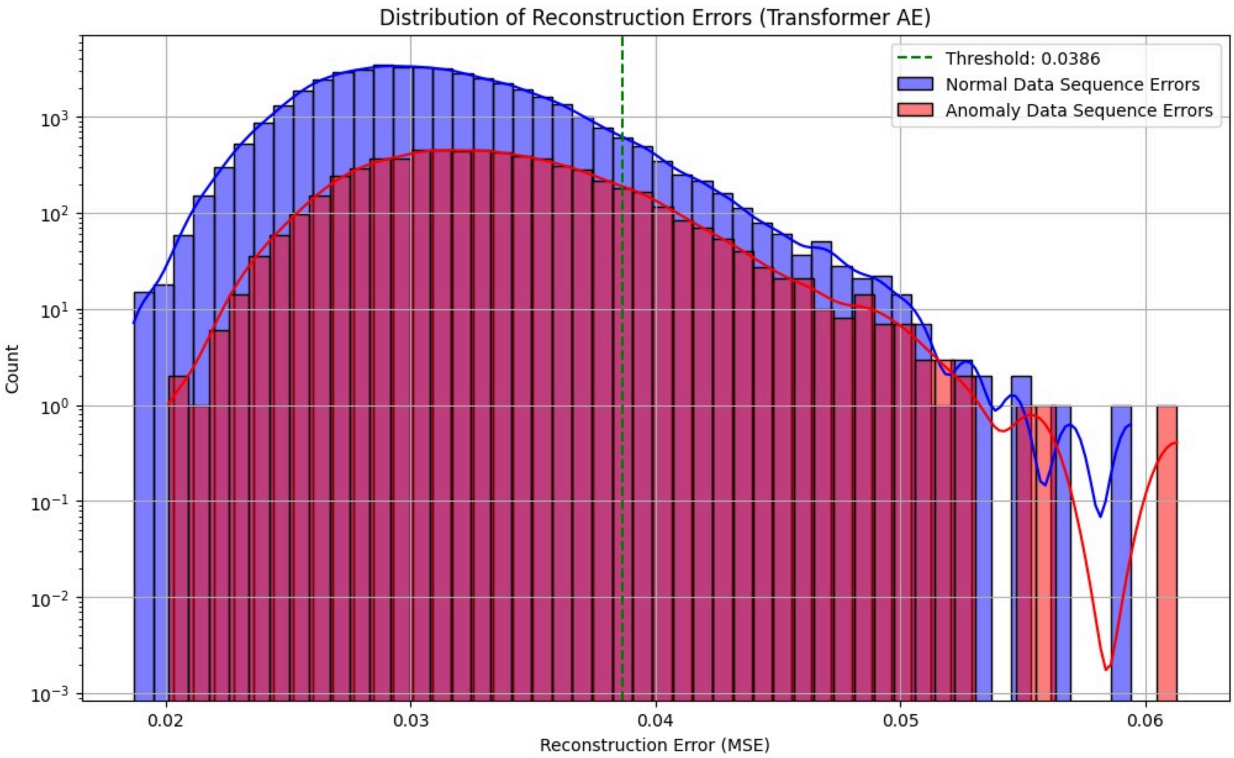


**Fig. 5:** Distribution of Reconstruction Errors (Transformer AE)

This histogram displays the distribution of reconstruction errors from a Transformer Autoencoder, showing two overlapping distributions: blue bars representing normal data sequence errors and red bars representing anomaly data sequence errors, both plotted on a logarithmic y-axis (count) ranging from 10^-3 to 10^4 against reconstruction error MSE on the x-axis (0.02 to 0.062). The normal data distribution (blue) forms a bell-shaped curve peaking around 0.03-0.035 MSE with a maximum count exceeding 2000 samples, spanning approximately 0.02 to 0.06 MSE, while the anomaly distribution (red) peaks slightly earlier around 0.03 MSE with a maximum count of 400-500 samples. A green dashed vertical line marks the decision threshold at MSE = 0.0386, strategically positioned to separate normal from anomalous sequences. The substantial overlap between both distributions indicates that reconstruction error alone provides moderate but imperfect separation, with the 0.0386 threshold representing an optimal trade-off point for classification decisions between normal and anomalous data sequences.

## V. CONCLUSION AND FUTURE WORK

This paper proposed a unified architecture for real-time analytics using Microsoft Fabric OneLake, addressing the challenges of scalable data integration, real-time processing, and intelligent anomaly detection in modern cloud-based systems. By leveraging OneLake as a centralized, time-aware storage layer and integrating a Transformer Autoencoder as an intelligent analytics component, the framework enables seamless ingestion, processing, and analysis of high-volume streaming data within a single unified platform.Using a smart grid real-time load monitoring dataset, the proposed architecture demonstrated strong capability in modeling complex temporal dependencies and non-stationary behavior inherent in multivariate time-series data. The Transformer Autoencoder effectively learned normal operational patterns and detected anomalies through reconstruction-based analysis. Experimental results showed that the proposed approach outperforms traditional baseline models, including Linear Regression, LSTM, GRU, and Isolation Forest, achieving superior accuracy, precision, recall, and F1-score. Additional evaluations using confusion matrix analysis, ROC–AUC, and precision–recall curves further confirmed the robustness and reliability of the proposed system.

Beyond predictive performance, this study highlights the practical relevance of Microsoft Fabric OneLake for enterprise-scale real-time analytics. The unified architecture simplifies data management, improves scalability, and supports automated alerts and monitoring, making it well-suited for real-world deployment in data-intensive environments. Future work will focus on extending the proposed framework to additional real-time application domains to evaluate its generalizability. Enhancements such as adaptive thresholding mechanisms and integration of explainable AI techniques will be explored to improve transparency and trust in anomaly detection decisions. Furthermore, large-scale deployment studies addressing latency, cost efficiency, and multi-cloud interoperability within Microsoft Fabric environments represent promising directions for continued research.

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