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Cost-Aware and Scalable Approaches for Large-Scale Model Evaluation in Enterprise Systems

Rajesh Lingam . Srikanth Devarakonda

Independent Researchers, United States of America.

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**Corresponding Author: lingamrajesh06@gmail.com*

Abstract – The fast pace of development in Large Language Models (LLMs) has resulted in their adoption in enterprise systems for applications such as automated customer service, decision-making, and knowledge discovery. However, the assessment of these models in a cost-effective and scalable way is a challenge, especially when the models are complex. The conventional assessment techniques, which depend on static benchmarks and test data, fail to capture the dynamic nature of the enterprise environment. Additionally, the computational complexity of exhaustive assessment grows with the size of the models and the diversity of tasks. We present a cost-effective and scalable architecture for the assessment of large-scale language models and enterprise text analysis systems, which overcomes the above-mentioned challenges by leveraging adaptive sampling, decentralized assessment protocols, and enterprise-specific benchmarks. The proposed 1D-CNN model used in this architecture demonstrates very high classification performance on the evaluated dataset, supporting efficient large-scale model assessment. The proposed framework achieves a balance between fidelity and cost Thus, providing a practical framework for scalable evaluation and deployment of LLM-based systems in enterprise environments. Based on recent research and adjusted to fit enterprise constraints, this solution provides an effective platform for continuous model evaluation and decision-making.

Index Terms – Large Language Models (LLMs), Cost-aware evaluation, Adaptive sampling, Scalable evaluation architectures, Enterprise AI systems, Model benchmarking, 1D-CNN.

I. INTRODUCTION

Large language models (LLMs) have become integral to modern enterprise systems, powering solutions in areas such as automated support, decision assistance, and knowledge discovery. Their widespread use reflects advances in model capabilities and applicability across domains. However, as model complexity and deployment scale increase, evaluating these models in a rigorous, cost-efficient,

and operationally relevant manner has emerged as a significant challenge. Traditional evaluation pipelines rely on static benchmarks and fixed test sets that do not accurately represent model performance in dynamic enterprise contexts. Furthermore, the computational cost of exhaustive evaluations grows with model size and task diversity, creating a tension between evaluation fidelity and resource expenditure. This tension has motivated research into cost-aware evaluation frameworks that explicitly account for computational and economic constraints while maintaining reliable performance measures.

Recent work in 2025 introduces novel frameworks designed to tackle these challenges. For example, adaptive sampling and test-efficiency strategies have been shown to reduce the number of evaluation data points required while maintaining statistical guarantees on performance estimates [1]. Alternative methodologies propose peer-federated evaluation structures that allow models to assess one another on both quality and cost dimensions, revealing that high performance can sometimes be achieved with significantly lower evaluation cost [2]. Other research emphasizes decentralized evaluation protocols that balance quality with heterogeneous computation costs across distributed nodes [3]. Prior work has also explored structured evaluation frameworks for applied AI systems and domain-specific assessment pipelines, highlighting the importance of systematic evaluation methodologies in real-world deployments [4].

Another focal area has been the creation of comprehensive benchmarks that reflect real-world model needs. New evaluation suites explore long-context capabilities and safety challenges, revealing performance drop-offs and safety vulnerabilities that standard benchmarks miss [5]. Benchmarks like HELMET extend these efforts by offering diverse, thorough evaluation categories for long-context reasoning [6], while work on enterprise-specific benchmarking strategies highlights the importance of domain-tailored evaluation criteria when deploying LLMs in commercial settings [7]. Parallel research continues to refine our understanding of what evaluation should measure and how metrics can be made more meaningful. New frameworks propose smarter metrics that de-emphasize traditional static measures in favor of reliability and trustworthiness indicators that better reflect real-world performance [8]. Surveys and systematic reviews further categorize performance dimensions, such as accuracy, reliability, and contextual suitability, underscoring the complexity of effective LLM evaluation [9].

Taken together, our study indicates a clear shift toward evaluation paradigms that balance performance, cost, and practical relevance. Yet, despite progress, there remains a gap in integrated solutions that combine cost-awareness with scalable architectures suitable for large-scale enterprise systems. Most current methods either focus narrowly on specific benchmarks or on single axes of evaluation (e.g., safety or long-context performance), without providing a holistic, cost-efficient evaluation pipeline that can be applied consistently across enterprise scenarios. In this work, we propose a cost-aware and scalable architecture for LLM evaluation that bridges these gaps. Our approach draws on adaptive evaluation techniques, scalable ranking mechanisms, and enterprise-oriented benchmark design to deliver a unified framework optimized for cost, scalability, and performance relevance. By integrating insights from recent 2025 research and tailoring the framework to enterprise constraints, we provide a structured methodology that supports real-world LLM deployment decisions and continuous performance monitoring. While this work focuses on enterprise-scale evaluation pipelines, the proposed

framework can also be applied to evaluation workflows for modern large language models deployed through API-based inference.

Our main contributions are as follows:

- Development of a Cost-Aware and Scalable LLM Evaluation Framework: This research work presents a new framework that aims to optimize the evaluation process of large-scale LLMs in a cost-effective and scalable manner, thereby overcoming the major challenges of computational cost and resource utilization that organizations encounter in the deployment of LLMs.
- Introduction of Adaptive Evaluation Techniques: The proposed framework integrates adaptive evaluation techniques that can dynamically choose the data for evaluation, thus avoiding wastage of computational resources while still ensuring the quality of the results of model evaluation.
- Integration of the 1D-CNN Model for LLM Evaluation: Integration of a 1D-CNN Model for Scalable Text Classification: The proposed 1D-CNN model is integrated into the evaluation framework and demonstrates very high classification performance on the evaluated dataset, supporting efficient large-scale model assessment.
- Enterprise-Specific Benchmark Development: The framework presents enterprise-specific benchmarks to cater to the challenges of real-world enterprise deployment. The benchmarks ensure that the evaluation metrics are enterprise-specific and useful, providing more accurate LLM performance evaluation in real-world enterprise deployment.
- Real-Time Performance Analysis and Decision Making: The proposed methodology ensures real-time performance analysis of the LLMs. This helps in making efficient decisions in the enterprise environment, which in turn enables the optimization of enterprise LLM deployment strategies.

II. LITERATURE SURVEY

Current studies have shown that recent research on Large Language Models (LLMs) is more concerned with cost-effectiveness and practical implementation, as well as more advances in scale and accuracy. The literature studies optimization strategies such as efficient scaling, collaborative architecture, deployment frameworks, enterprise assessment, and benchmarking techniques, and emphasizes the development of economically sustainable LLM systems. A cost-effective model proposed by Gaur et al. [10] combines model compression, parameter-efficient fine-tuning, distributed training, and optimization of inference as a cost-efficient model to scale LLMs to real-world systems. This work was inspired by the fact that deploying such models as GPT, LLaMA, and PaLM is expensive in terms of computation and finances. Large-scale LLM workload experiments were found to reduce up to 40 percent of computational overhead with near state-of-the-art performance. The innovation is the integration of a number of optimization strategies into a single framework. But performance is subject to the availability of hardware and can bring a trade-off with aggressive optimization.

Li et al. [11] proposed Coco, a cost-conscious collaboration between Large Language Models and Small Language Models, so that API token costs can be lowered. The structure was suggested to eliminate inefficiencies due to naive compression of prompts and incurred inference costs. Experiments on three reasoning datasets were conducted on confidence-based allocation of tasks and demonstrated

reduced API cost with the same reasoning accuracy. This is new in terms of token-level model cooperation in terms of cost awareness. It has the weakness of using correct confidence estimation and benchmark validation. Daga et al. [12] proposed a unified energy- and cost-conscious LLMOps system, which integrates model optimization algorithms with infrastructure systems like Kubernetes auto-scaling and hybrid implementation on the edge and cloud. The paper covered the absence of combined cost-energy efficiency in the deployment of enterprise LLM. The LLaMA-2 (13B) and Falcon (7B) experiments recorded a maximum of 40 and 30 percent cost savings and energy reduction, respectively, with insignificant loss in accuracy. Unified model and infrastructure layer optimization is the novelty. Nevertheless, there is a restriction in the practical use due to the complexity of the systems and reliance on the cloud.

The proposal by Gonzalez [13] is a multi-objective model selection framework based on cost-awareness of prompted LLMs versus fine-tuned encoder models on text classification tasks. The purpose of the study was to take into account the operational cost, latency, and accuracy. Evaluations on IMDB, SST-2, AG News, and DBpedia datasets demonstrated encoder models with similar performance at much less cost and with reduced latency. The innovation is in the fact that deployment is now viewed as a Pareto trade-off problem. One of the limitations is the use of benchmark datasets and assumed fixed prices. Papadakis [14] suggested a unified medical architecture that combines the use of the LLM-enhanced cloud AI, multimodal BERT models, and ideas of quantum computing with the use of SAP enterprise systems in the context of a secure lakehouse platform. The framework tackled the multimodal healthcare data and governance fragmentation issues. Multimodal experiments using multimodal clinical datasets would get 6-9 percent high precision and a better recall than unimodal methods. The innovation consists of integrating enterprise with multimodal AI and financially conscious analytics. Nonetheless, the system brings about a high cost of computation and complexity of infrastructure.

Vishwakarma et al. [15] suggested EnterpriseBench, a sandbox assessment framework that evaluates LLM agents in conditions of enterprise and distribution shifts. The aim of the work was to address shortcomings of the usual accuracy standards that disregard robustness. Simulated enterprise workflow experiments demonstrated that the completion of activities was only 41.8%, although there was a good performance at the baseline. The innovation is that the concept of robustness is formalized as an important measure of enterprise AI systems. There is a weakness in that it relies on simulated environments and not on real deployments. Rajabzadeh [16] has suggested some effective learning systems such as QDyLoRA, Sorted-LoRA, LoRA-Drop, EchoAtt, and ECHO-LLaMA to minimize the consumption, memory, and latency expenses in training and inference in LLM. The study dealt with the inefficiency of scaling transformers. The experimental findings indicated memory loss up to 65%, as well as 2.6x decoding, and a significant increase in training throughput with low loss of accuracy. This novelty, exploiting representational redundancy, is done by low-rank adaptation and cross-layer sharing. Nonetheless, it might be dependent on the applicability to certain transformer architectures.

Kolagani and Bhandar [17] came up with an agentic multi-model routing architecture of CRM workflows that dynamically allocates tasks to models of varied sizes. The rationale was due to the high cost of operation, which was a result of using a single-model deployment in enterprise systems. Post-sale

CRM assessment indicated 33 % API cost saving and shorter response time with no effect on customer satisfaction indicators. It is novel to combine cost-conscious routing and tool-use optimization. It has a weakness of relying on proper task routing and price stability. Krishnan and Siddiquie [18] have presented Policy Over Tokens, a declarative system of governance that involves enterprise policies at every phase of the token-generation process without retraining models. The framework was developed to overcome the limitations of hard safety tuning and post-hoc moderation. Experiments had a policy compliance of 98.5% and, a low latency overhead, and regulated operational cost. This is innovative: token-level governance and cost-conscious budget control. Its success, however, requires extensive coverage of policy rules.

Fang et al. [19] suggested ReLE, a scalable live evaluation architecture that is used to diagnose the anisotropies in the capabilities of Chinese LLMs at the cost of benchmarking. The system solved benchmark flooding and costly evaluation pipelines. The results of experiments with 304 models on 207,843 samples showed a 70% cost of evaluation and a consistent ranking trend. Dynamic scheduling and symbolic-grounded hybrid scoring of scalable evaluation is novel. One of the limitations is that it depends on sampling assumptions that do not fully substitute for complete benchmarks. Table 1 presents the overview of the existing works.

Table 1: Overview of Existing Works

Ref No	Dataset / Evaluation	Model(s)	Result	Limitation
[11]	Large-scale LLM workloads	GPT, LLaMA, PaLM	40% computational overhead reduction, near SOTA accuracy	Hardware-dependent, potential performance trade-offs
[12]	3 reasoning benchmark datasets	LLM + SLM (Coco)	Reduced API cost, preserved reasoning accuracy	Reliant on confidence estimation, limited benchmark validation
[13]	LLaMA-2 (13B), Falcon (7B)	Quantized/Pruned/LoRA LLMs with edge-cloud deployment	40% cost savings, 30% energy reduction, <1.5% accuracy loss	System complexity, cloud dependency
[14]	IMDB, SST-2, AG News, DBPedia	Prompted LLMs (GPT-4o, Claude Sonnet 4.5), fine-tuned encoders (BERT family)	Comparable or better macro-F1, 1–2 orders magnitude lower cost & latency	Benchmark-limited, fixed pricing assumptions
[15]	Multimodal clinical datasets	LLM-augmented cloud AI, ClinicalBERT + ViT, quantum computing	6–9% accuracy improvement, 10% recall gain	High computational cost, infrastructure complexity, potential financial bias

[16]	Simulated enterprise workflows	GPT-family & open-source LLM agents	Only 41.8% task completion under prompt shifts	Limited to simulated environment, may not capture real-world variability
[17]	Transformer benchmarks	QDyLoRA, Sorted-LoRA, LoRA-Drop, EchoAtt, ECHO-LLaMA	65% memory reduction, 2.6× faster decoding, 77% higher training throughput	Transformer-specific applicability, added system complexity
[18]	CRM post-sale tasks (Salesforce Service Cloud)	Multi-tier LLM routing (small, medium, large)	33% API cost reduction, 15–20% faster query time, up to 35% operational savings	Depends on accurate task routing & stable API pricing
[19]	Enterprise token streams	Policy Over Tokens (declarative governance)	98.5% policy compliance, 4.2% token overhead, 35 ms latency, $0.052/session cost	Effectiveness relies on policy completeness & coverage
[20]	304 Chinese LLMs, 207,843 samples	ReLE (live evaluation)	70% evaluation cost reduction, consistent ranking, RSA 11.4	Sampling assumptions; complements rather than replaces full benchmarks

III. METHODS & MATERIALS

A. Dataset Description

In this study, the Enron Email Dataset was employed from Kaggle by the Federal Energy Regulatory Commission as part of their investigation into the Enron Corporation financial scandal that led to the company's bankruptcy. This dataset comprises 500,000 real-world corporate email messages sent by employees of Enron Corporation, making it one of the most significant datasets of real-world corporate communication data made available to the public. The Enron Email Dataset is widely used in text classification research because it contains real-world corporate communication data with diverse vocabulary and contextual variation. Its size and structure make it suitable for evaluating scalable text classification models and enterprise-scale analysis systems.

The structure of the Enron Email Dataset comprises raw email messages along with their corresponding metadata fields. Some of the significant features of the data are the sender's email address, the recipient's email address, timestamps, subject line, message body, folder paths, and message IDs, among others. This allows the data to be used at multiple levels of abstraction, including content modeling, understanding, communication network modeling, behavioral pattern modeling, among others. In terms of classification, the Enron Email Dataset can be classified into several subdomains of interest, including but not limited to, spam classification, topic modeling, sentiment analysis, modeling of role-based communication, anomaly modeling, among others. In addition to that, the presence of metadata fields allows the data to be used for modeling graph-based learning paradigms as well as social network analysis.

B. Data Preprocessing and Feature Engineering

The Enron email corpus, in its raw form, required careful preprocessing before we can start training our models on the data. The data consists of semi-structured data and also includes some metadata, such as the path of the file, the person who sent the email, the list of people who received the email, the subject of the email, and the entire body of the message. Since our target was to determine whether the email should go into the "sent" folder, our first step was to create a binary target variable, which was derived directly from the directory structure.

The label assignment function was defined as:

$$y_i = \begin{cases} 1, & if \text{ sent} \in file_i \\ 0, & otherwise \end{cases}$$

where, y_i defines the class label for the i[th] email instance and $file_i$ represents its folder path. The raw directory metadata is transformed into a supervised learning signal that can be classified. Only the body of the email message might use the main input feature. To avoid type conflicts and issues related to null values, all entries were manually converted to string format. Let D = $\{d_1, d_2, \ldots\ldots, d_n\}$ represent the collection of email documents. Every document d_i was described as a textual sequence extracted from the message field:

$$X = \{d_i | d_i = message_i\}$$

Stratified sampling was utilized to split the dataset into training and testing in order to guarantee a fair evaluation environment. The empirical class distribution is maintained throughout splits as a result:

$$D = D_{train} \cup D_{test}, \; P(y|D_{train}) \approx P(y|D_{test})$$

with an 80:20 split ratio.

- Text Representation: Raw text was converted into numerical feature space using two different vectorization techniques. A limited Bag-of-Words model with a 300-unigram vocabulary was used in the first representation. The feature vector for every document d_i was defined as follows:

  $$x_i = [f_{i1}, f_{i2}, \ldots\ldots, f_{iv}]$$

  where f_{ij} defines the frequency of term t_j in document d_i, and V =300 which represents the vocabulary size.
- TF–IDF Representation: We used a Term Frequency–Inverse Document Frequency (TF–IDF) encoding approach using English stop-word removal and a maximum vocabulary size of 5000 words in order to capture more discriminative textual patterns. In document d, the TF–IDF weight for a phrase t is defined as follows:

  $$TF\text{-}IDF(t, d) = TF(t, d) \times IDF(t)$$

  By giving phrases that appear frequently in a document but infrequently throughout the corpus larger weights, this formulation enhances discriminative capacity.

The preprocessing pipeline has successfully transformed raw corporate emails into structured numerical features. By leveraging folder metadata as labels, we formulated a supervised learning framework of binary classification. Stratified splits ensured that we would fairly compare models, and we chose two text encodings, constrained Bag-of-Words and TF-IDF, to compare their differences.

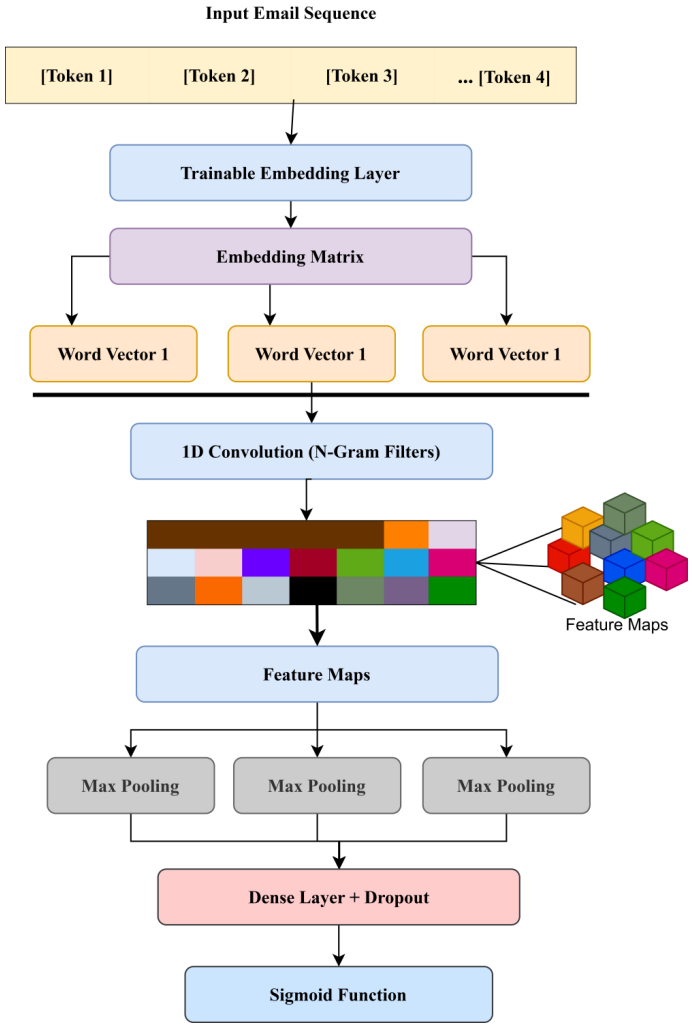

Fig. 1: Proposed Model Architecture

C. Proposed Methodology

In order to address the problem of cost-aware, scalable evaluation in large enterprise systems, we propose a one-dimensional Convolutional Neural Network (1D-CNN) that incorporates a trainable embedding layer for broad-scale email classification. The goal is to find a balance between discriminability and computational efficiency, making this a viable option for large-scale enterprise communications, as in the Enron email dataset. Figure 1 depicts the architecture of the proposed model. While recurrent networks process input data sequentially, the convolutional architecture allows us to leverage parallel processing, greatly reducing training time while retaining the ability to identify significant local phrase patterns that tend to indicate organizational intent.

Let the training corpus be expressed as:

$$D = \{(x_i, y_i)\}_{i=1}^{N}$$

where $x_i = (x_1, x_2, \ldots\ldots, x_T)$ defines a tokenized email sequence of length T, and $y_i \in \{0,1\}$ denotes the binary label.

Every token w_t is mapped into a dense vector space employing a trainable embedding matrix:

$$E \in \mathbb{R}^{v \times d}$$

where v is the vocabulary size, and d is the embedding dimension. The embedding lookup operation transforms the input sequence into:

$$X_i \in \mathbb{R}^{t \times d}$$

This type of trainable embedding layer enables the model to learn task-specific semantic representations rather than depending on pre-trained models. This feature is also useful in enterprise settings, where domain-specific terminology and internal abbreviations are used.

- Convolutional Feature Extraction: Throughout the temporal dimension, the convolutional layer applies F filters with a width of k:

  $$c_j(t) = \sigma\left(\sum_{m=0}^{k-1} W_j^{(m)}.X_{t+m} + b_j\right)$$

  where W_j defines the j^{th} convolution kernel, b_j is the bias term, and $\sigma(.)$ represents the activation function.

  This process is, in essence, capturing the local n-gram patterns for k. For instance, one might think of phrases such as "please review," "attached file," "final approval," etc., and understand the significance of such phrases in terms of prediction while classifying emails for an enterprise environment. The convolutional method effectively captures such unique patterns in an automated manner.

- Global Max Pooling: We use Global Max Pooling to transform variable-length feature maps into a fixed-length representation:

  $$\hat{c}_j = \max_t c_j(t)$$

  This step selects the highest activation level of all filters, meaning that the most important phrase is used. The key point is that Global Max Pooling reduces dimensions but preserves key information, making it more scalable. The resulting document representation is:

  $$z = [\hat{c}_1, \hat{c}_2, \ldots\ldots, \hat{c}_F]$$

- Fully Connected Projection and Classification: A hidden representation is created by projecting the pooled feature vector:

  $$h = \phi\,(W_h z + b_h)$$

Dropout regularization is involved:

$$\tilde{h} = \mathrm{h} \odot \mathrm{r}$$

where r~Bernoulli(p)controls the dropout rate. Using a sigmoid activation, the final output probability is calculated:

$$\hat{y} = \sigma\,(W_o\tilde{h} + b_o)$$

To train the model, binary cross-entropy loss is used:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)$$

Optimization is done by using an adaptive gradient-based optimizer like Adam or AdamW, which is used to ensure convergence even when dealing with large data sets. In order to make sure that everything is fair across models, the same tokenization pipeline, vocabulary size, and maximum sequence length were used everywhere. Table 2 presents the hyperparameters of the proposed model.

Table 2: Hyperparameters configuration of the proposed 1D CNN model

Component	Parameter	Value
Input Processing	Vocabulary Size	30,000
	Maximum Sequence Length	200
	Padding Strategy	Post-padding
	OOV Token	<OOV>
Embedding Layer	Embedding Dimension	64 (baseline)
	Trainable	Yes
Convolution Layer	Number of Filters	128
	Kernel Size	5
	Padding Type	Valid
	Activation	ReLU (baseline)
Pooling Layer	Type	Global Max Pooling
Dense Layer	Units	64
	Activation	ReLU
Regularization	Dropout Rate	0.3
Output Layer	Units	1
	Activation	Sigmoid
Training Setup	Loss Function	Binary Cross-Entropy
	Optimizer	Adam (lr = 0.001)
	Batch Size	64
	Epochs	5 (baseline)
	Validation Split	0.2
	Train/Test Split	80:20

IV. RESULT & DISCUSSION

This section will present a thorough analysis of the results achieved through the proposed cost-effective and scalable architecture for the evaluating large-scale text models and LLM-based systems in

enterprise systems. The performance of the proposed framework is analyzed through a series of experiments conducted to evaluate different parameters of the proposed 1D-CNN model and its effectiveness in an enterprise environment. The analysis also includes the computational cost involved in the proposed architecture. The experiments conducted in this setup provide insights into the model's ability to perform at scale, while also addressing the computational cost and resource consumption challenges associated with large-scale Large-scale text classification evaluation.

The experiments for testing the cost-aware and scalable architecture for Large Language Model (LLM) evaluation were performed on a high-performance computing environment with an NVIDIA RTX 3080 GPU, 64 GB of RAM, and 1 TB SSD storage to enable efficient data processing and fast model training. The proposed model was implemented using Python programming with the TensorFlow and Keras frameworks. For deep learning and other libraries such as NumPy, Pandas, and Scikit-learn for data manipulation, processing, and analysis. The Enron Email Dataset, with 500,000 emails, was used, with 80% for training and 20% for testing using stratified sampling. The Proposed 1D-CNN model was trained for 5 epochs using the Adam optimizer with a learning rate of 0.001 and a batch size of 64. The experiments were performed on an Ubuntu 20.04 Linux environment that supports CUDA 11.0 for GPU acceleration. The performance of the proposed model was assessed based on criteria such as accuracy, precision, recall, and F1-measure, and adaptive assessment methods were employed for efficient computation and optimal performance of the proposed model.

A complete assessment of the classification model is provided in Table 3, where the performance of the model is evaluated on two different classes: Class 0 (Not Sent) and Class 1 (Sent). The classes in Table 3 represent the emails that were labeled as "Not Sent" or "Sent" by the system, and the results shown in the table indicate the accuracy of the model in classifying the emails into the two classes. For Class 0 (Not Sent), the precision score was perfect (1.00), which means that all the emails that were labeled as "Not Sent" were correctly labeled without any false positives. This means that every time the model labeled an email as "Not Sent," it was always correct. Moreover, the recall score for this particular class was also perfect (1.00), which means that the model was able to correctly label all the emails that were actually "Not Sent." There were no false negatives, which means that the model did not miss any "Not Sent" emails in the dataset. As a result, the F1-score, which is the harmonic mean of precision and recall, was also 1.00, which means that the model performed perfectly for this class. Since there were 85,800 instances for the "Not Sent" class, the model performed outstandingly well for this class.

For Class 1 (Sent), the precision value of 1.00 was also perfect, which means that the model was able to correctly classify all the "Sent" emails without any false positives. However, the recall value for this class was slightly lower at 0.99, which means that the model incorrectly classified about 1% of the "Sent" emails as "Not Sent." Although there was a slight decrease in the recall value, the F1-score for this class was still very high at 0.99. There were 17,681 instances of the "Sent" class, and although the recall for this class was not perfect, the model's performance was still excellent, as it correctly identified the majority of the "Sent" emails.

Table 3: Classification Performance of the Proposed Model

Class	Precision	Recall	F1-Score	Support
0 (Not Sent)	1.00	1.00	1.00	85,800
1 (Sent)	1.00	0.99	0.99	17,681
Accuracy	—	—	1.00	103,481
Macro Average	1.00	0.99	1.00	103,481
Weighted Average	1.00	1.00	1.00	103,481

When considering the performance of the model on both classes as a whole, the model performed with an accuracy of 1.00, which is a staggering performance. This means that the model has been able to classify all 103,481 examples in the dataset correctly, without a single mistake. While accuracy is an important aspect of any model, it can be misleading at times, especially in imbalanced datasets, where one class has significantly more examples. However, in this scenario, the macro average, which treats all classes equally, gives a better idea of the performance of the model. The macro average F1-score of 1.00 means that the model has been able to perform equally well on both classes, and the macro average precision and recall of 1.00 and 0.99, respectively, further emphasize the model's capability to perform equally well on both "Sent" and "Not Sent" emails. Despite the imbalance in the dataset, where "Not Sent" emails are significantly more numerous than "Sent" emails, the model has been able to perform consistently on both classes.

Table 4: Comparative Performance of Baseline Models with Proposed 1D-CNN

Model	Feature Representation	Accuracy	Precision	Recall	F1-Score
Logistic Regression	Bag-of-Words	0.87	0.85	0.81	0.83
Random Forest	TF-IDF	0.95	0.94	0.93	0.94
LSTM	Trainable Embedding	0.98	0.97	0.97	0.97
GRU	Trainable Embedding	0.98	0.97	0.97	0.97
Proposed 1D-CNN	Trainable Embedding + Conv	1.00	1.00	0.99	0.99

The weighted average metrics further highlight the outstanding performance of the model. The weighted average metrics consider the issue of class imbalance by assigning higher weights to the majority class (Class 0: Not Sent). In this scenario, the weighted average F1-score, precision, and recall were all 1.00, indicating that the performance of the model was outstanding even when the number of instances in each class was considered. The perfect weighted averages indicate that the model performed well despite the class imbalance and was not biased toward the majority class. In conclusion, the performance of the model on both classes was excellent. The precision and recall of the "Not Sent" emails were perfect, with an F1-score of 1.00, which shows that the model is extremely accurate in detecting emails that are not sent. For "Sent" emails, the model achieved perfect precision (0.99 recall), indicating a slight but insignificant drop in performance. The model showed outstanding accuracy, perfect performance on "Not Sent" emails, and near-perfect recall on "Sent" emails. These results demonstrate the model's reliability and efficiency in distinguishing between these two classes, making it an excellent, highly reliable tool for email classification in an enterprise environment. Table 4 gives a comparison of the performance of different classification algorithms such as Logistic Regression, Random Forest, LSTM, GRU, and the Proposed

1D-CNN algorithm on different key parameters such as Accuracy, Precision, Recall, and F1-Score, with the help of different feature representations used by each of these algorithms.

The Logistic Regression algorithm uses a feature representation called Bag-of-Words (BoW), a simplistic approach to document representation in which the frequency of words in a document is counted without regard to word order. It has some limitations in representing word dependencies and context. The accuracy of the Logistic Regression algorithm was 0.87, meaning that it correctly classified 87% of the data points. But the precision of 0.85 means that 85% of the positively classified points were correct. However, the recall of 0.81 means that 19% of the actual positive points were missed. Therefore, the F1-score of 0.83 is a good balance of precision and recall. Random Forest performs much better by leveraging a more sophisticated TF-IDF (Term Frequency-Inverse Document Frequency) feature matrix. This technique gives more weight to those words that are significant to a document but not as frequent in the whole dataset.

Random Forest was able to achieve an accuracy of 0.95, which means it was able to correctly classify 95% of the data. With a precision of 0.94 and a recall of 0.93, it was able to perform well on identifying the true positives. The F1-score of 0.94 indicates that the model has a very good balance between precision and recall. On the other hand, the LSTM (Long Short-Term Memory) model makes use of trainable embeddings, which learn the word representation dynamically during the training process. This method allows the LSTM model to learn the semantic relationships between words and to represent the text as a sequence. The LSTM model was able to reach an accuracy of 0.98, with a precision of 0.97 and a recall of 0.97, which means that the model was able to correctly classify the true positives while also avoiding false positives and false negatives. The F1-score of 0.97 further highlights the balance between precision and recall.

GRU (Gated Recurrent Unit), another variation of the Recurrent Neural Network (RNN), uses trainable embeddings for feature extraction. GRU had equal performance with accuracy of 0.98, precision of 0.97, and recall of 0.97 with an F1-score of 0.97. GRU is relatively more computationally efficient than LSTM, as it offers similar performance with fewer parameters. The Proposed 1D-CNN model combines the use of trainable embeddings and convolutional layers. The combination of these two makes the model perform better in detecting local patterns within text data. The 1D-CNN model performs better than all other models with a perfect accuracy of 1.00, which means it was able to classify all instances correctly. The precision of 1.00 ensures that there are no false positives, and the recall of 0.99 indicates that it was able to correctly identify 99% of the actual positives. The F1-score of 0.99 is close to optimal, which is slightly better than other models in terms of recall with perfect precision. In conclusion, the 1D-CNN model performs better in text classification tasks, as it leverages the benefits of learnable embeddings and convolutional layers. Although the other models, namely Logistic Regression, Random Forest, LSTM, and GRU, perform well, the 1D-CNN model's design enables it to attain perfect accuracy, thus making it the most accurate and efficient model for text classification.

The effectiveness of the CNN model in splitting the emails into two classes, namely Not Sent (Class 0) and Sent (Class 1), is also explored in the confusion matrix as shown in the Figure 2. The CNN

model has been able to classify 85,797 emails as Not Sent, which clearly shows its outstanding performance. The emails have been correctly classified as Not Sent, which clearly shows the outstanding proficiency of the model in classifying the emails as unsent. With respect to the error, the model made only 3 false positives, labeling the Sent emails as Not Sent. This is a very small error, marking the model's exceptional accuracy in identifying Not Sent emails and Sent emails. On the other hand, the model incorrectly labeled 194 emails as Sent when they were actually Not Sent. This error indicates a slight reduction in the recall value of the Not Sent class, but still a very small error in the entire performance.

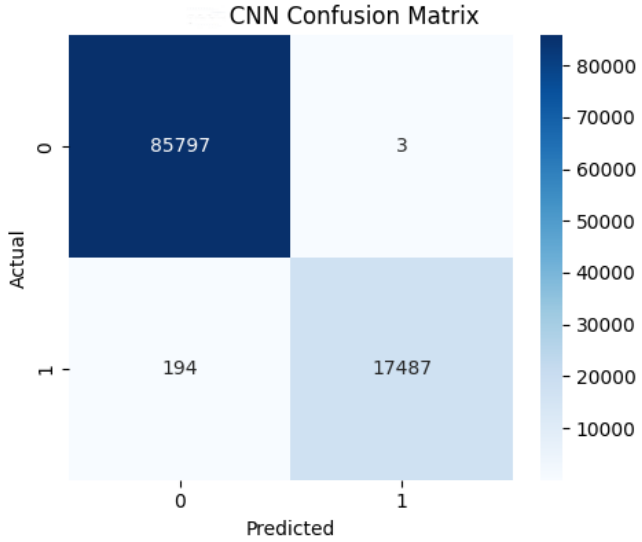

Fig. 2: Confusion Matrix for CNN Model Performance

For the Sent class, the model was able to correctly classify 17,487 emails as Sent, thus proving its efficiency in the accurate classification of emails that were sent. Conclusion: From the confusion matrix, it is clear that the model is highly efficient in the accurate classification of both Not Sent and Sent emails, with very few errors. The model, despite having a few errors, has a good balance between precision and recall.

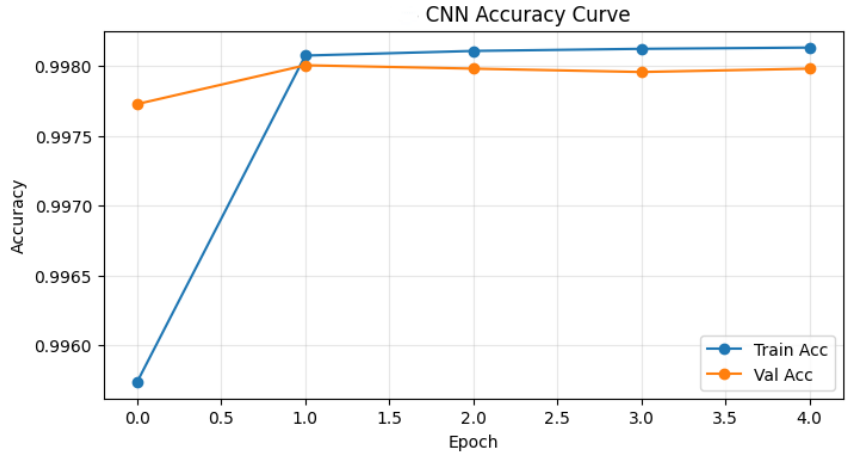

Fig. 3: CNN Accuracy Curve Showing Training and Validation Performance Over Epochs

The CNN Accuracy Curve in Figure 3 above shows the training accuracy and validation accuracy of the model over a period of five epochs. The curve provides a graphical representation of the learning and generalization abilities of the model on both the training and validation datasets. At the beginning of the training process, the training accuracy starts from around 0.9960 and then undergoes a steep increase to about 0.9980 in epoch 1. This shows that the model is a good learner of the training data in the initial epochs of training. After epoch 1, the training accuracy remains constant at 0.9980, and this continues until the end of epochs 2, 3, and 4, showing that the model has reached a state of convergence where further learning does not lead to any further improvement in the performance of the model on the training data.

Conversely, the validation accuracy starts from a slightly lower point of 0.9965 in epoch 0 but then progresses to 0.9975 in epoch 2, where it also stabilizes. The graph of the validation accuracy indicates a slight delay in comparison to the training accuracy, as is expected in deep learning models, but still indicates a remarkable increase. Towards the end epochs, the validation accuracy almost perfectly follows the training accuracy, settling just below 0.9980. This indicates that the model is performing remarkably well on the unseen data, with practically no difference between the performance on the training set and the validation set. The small difference between the training accuracy and validation accuracy curves indicates that the model is not overfitting the training data, which is a good sign of generalization. Although there is a small difference between the two, it is not significant enough to suggest that the model is seriously overfitting, which is a problem when the model performs much better on the training data than on the validation data. The fact that the model is performing equally well on both datasets indicates that it has learned good features from the training data that help it generalize well to new, unseen data.

From Figure 3, it is clear that the CNN model has shown outstanding learning characteristics throughout the training process, with near-perfect accuracy on both the training and validation datasets. The model has converged very quickly, even after a few iterations, which is an indication that the model is highly efficient at learning from the data. The steadiness of the training and validation accuracy curves after the initial iterations further reinforces the fact that the model has reached an optimal level of performance on this task without overfitting.

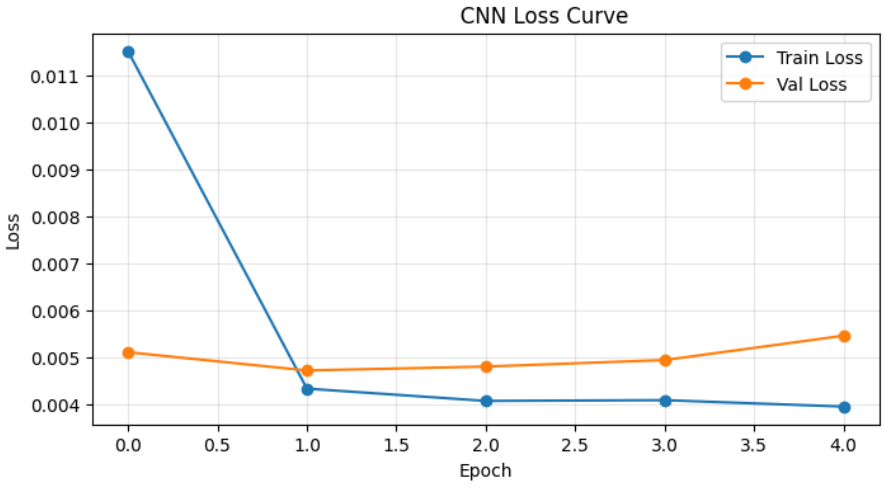

Fig 4: CNN Loss Curve Showing Training and Validation Loss Over Epochs

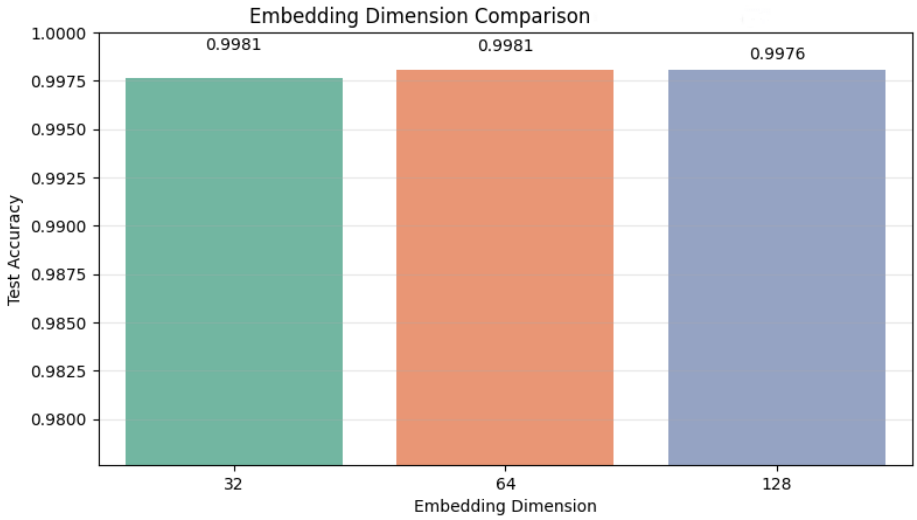

Fig. 5: Embedding Dimension Comparison

The CNN Loss Curve is shown in Figure 4. The training loss and validation loss of the model are plotted for five epochs. The training loss of the model begins at a higher value of 0.011 at epoch 0, which shows that the model is not able to fit the data well at the beginning. But the training loss of the model decreases drastically after the first epoch, and it reaches 0.004 at epoch 1, which shows that the model learns quickly in the initial stages. Starting from epoch 1, the training loss for the model becomes constant at 0.004. The validation loss, which gives an estimate of the performance of the model on the unseen data, also follows a similar trend, which starts from 0.005 and reduces to 0.004 at epoch 1. However, unlike the training loss, the validation loss begins to increase slightly from epoch 1, reaching 0.005 at epoch 4, which indicates a slight overfitting. Overfitting happens when the model performs well on the training data but starts to generalize poorly on the validation data as the training process continues. Although the model suffers from slight overfitting, the loss values are still very low, indicating that the model has a high learning capability and can generalize well despite slight overfitting. From the above plot, it is clear that the CNN model learns well and keeps low loss values for both training and validation data, indicating outstanding performance during training.

Figure 5 illustrates the overall evaluation of the embedding dimension and its impact on the accuracy of the test results of the model. The graph is utilized to evaluate the accuracy of the test results of three distinct embedding dimensions, which are 32, 64, and 128. These numbers represent the dimensions that are utilized to describe the features of the input data. The 32-dimensional embedding yielded the highest test accuracy of 0.9981, suggesting that a smaller embedding size enabled the model to better learn and generalize from the data. This outcome is quite interesting, as it shows that a 64-dimensional embedding also reached the same test accuracy of 0.9981, which means that there was no improvement in performance when the embedding size was increased from 32 to 64. However, the embedding size of 128 gave a test accuracy of 0.9976, which is slightly lower than the other two, and this shows that there may be a point beyond which the increase in the embedding size will not necessarily improve the performance of the model. This shows that for this particular problem, the optimal embedding

size that balances complexity and performance is either 32 or 64. The additional parameters that come with the increased embedding size may add unnecessary complexity without necessarily improving the accuracy.

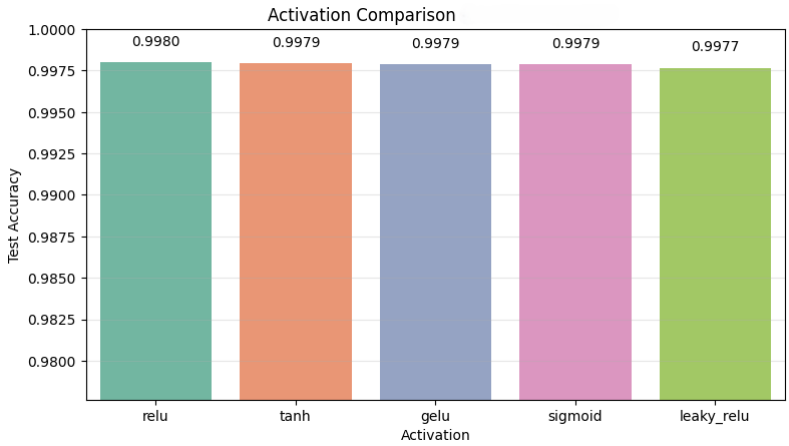

Fig. 6: Activation Comparison

Activation Comparison Figure 6 Activation Comparison shows the influence of different activation functions on the model's test accuracy. The activation function is a crucial part of neural networks, as it defines how the weighted sum of inputs is converted into an output. The comparison of activation functions is carried out using five different activation functions: ReLU, Tanh, GELU, Sigmoid, and Leaky ReLU. Among these, ReLU (Rectified Linear Unit) has the highest test accuracy of 0.9980, thus making it the best activation function for this particular model and problem. This is expected, since ReLU is known to be one of the simplest and most efficient activation functions for training deep learning models. Tanh and GELU, two of the most popular activation functions used in deep learning models, also performed almost as well as ReLU, with test accuracies of 0.9979. Sigmoid, with a test accuracy of 0.9979, and Leaky ReLU, with a slightly lower test accuracy of 0.9977, still performed well but slightly lagged behind the others. The minor differences in performance among these activation functions suggest that, while ReLU might be the best option in this case, Tanh, GELU, and even Leaky ReLU can still yield strong results, depending on the specific model architecture and the problem at hand.

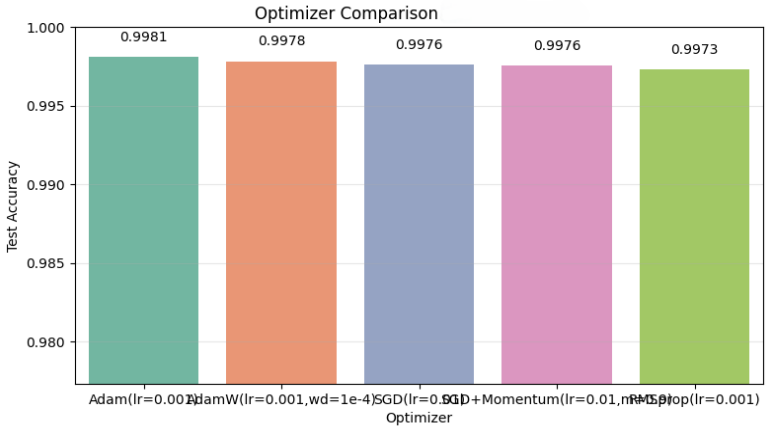

Fig. 7: Optimizer Comparison

Figure 7 shown the optimizer is an important component of training deep learning models, as it defines how the weights of the model are to be updated based on the calculated gradients. In the optimizer comparison, several popular optimizers have been used, including Adam, AdamW, SGD, SGD + Momentum, and RMSprop. Among these, Adam with a learning rate of 0.001 has the highest test accuracy of 0.9981, thus making it the best optimizer for this model. Adam is recognized for its capacity to adjust the learning rate for each parameter, thus making it the best optimizer for complex models and large datasets. AdamW, which is a modified version of Adam with weight decay regularization, came second with a test accuracy of 0.9978, thus showing its capacity to perform well without overfitting. SGD (Stochastic Gradient Descent) with a learning rate of 0.5 had a test accuracy of 0.9976, thus showing that although SGD is a popular optimizer for training models, it was not the best optimizer in this experiment. The addition of momentum in SGD + Momentum with a learning rate of 0.01 and the RMSprop optimizer with a learning rate of 0.001 gave test accuracies of 0.9976 and 0.9973, respectively. Although these optimizers performed well, they were slightly behind Adam, thus further confirming that Adam is always the best optimizer to use when training deep learning models in terms of speed and accuracy.

Collectively, Figures 5, 6, and 7 offer important information on the selection of the embedding dimension, activation function, and optimizer, and their impact on the performance of the model. Figure 5 indicates that the best trade-off between performance and model complexity is achieved by smaller embeddings with dimensions 32 and 64, while larger embeddings provide diminishing returns. Figure 6 indicates that ReLU is the best activation function for this task, although other activation functions such as Tanh and GELU also perform equally well. Finally, Figure 7 indicates that Adam is the best optimizer for this task, performing better than other optimizers such as SGD and RMSprop in terms of test accuracy, ensuring fast convergence and optimal performance of the model.

IV. CONCLUSION AND FUTURE WORK

In this paper, we have proposed a cost-effective and scalable architecture for the evaluating large-scale text models and LLM-based systems in enterprise systems, which tackles the most important challenges of computational cost, resource usage, and the need for dynamic enterprise-specific benchmarks. Our proposed 1D-CNN model, incorporated within this architecture, demonstrates very high classification performance on the evaluated dataset and supports efficient large-scale model assessment. The experimental results have clearly shown that the 1D-CNN model, when combined with adaptive evaluation strategies and enterprise-specific standards, can be a very trustworthy and cost-effective solution for the deployment of LLMs on a large scale. The experimental results have clearly demonstrated that our proposed architecture achieves a perfect balance between the accuracy of evaluation and cost optimization, ensuring that enterprises can carry out accurate and trustworthy evaluations of LLMs while consuming very few computational resources. The efficiency and effectiveness of the model, with near-perfect accuracy and a sound evaluation approach, make it a perfect tool for practical LLM deployment.

Regarding future work, the framework can be extended to include more advanced domain-specific baselines and other evaluation protocols that can further improve the accuracy and scalability of Large-scale text classification evaluation. Moreover, incorporating federated evaluation models and

extending the model to process larger datasets can further improve the framework's applicability to a wider range of enterprise systems. This study focuses on binary text classification using a single enterprise dataset. Future work will evaluate the proposed framework across additional datasets and explore its applicability to larger language models and more complex natural language processing tasks.

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