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A Transformer and Deep Embedded Clustering Based Framework for Dynamic Workload Characterization

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Abstract:

Dynamic workload characterization plays a critical role in modern data centers and cloud computing environments, where efficient resource allocation and workload-aware scheduling are essential for maximizing system performance and energy efficiency. Traditional workload characterization approaches based on statistical methods and conventional machine learning models often fail to capture complex temporal dependencies and hidden workload patterns present in large-scale hardware performance datasets. To address this limitation, this paper proposes a novel Transformer and Deep Embedded Clustering (TDEC)-based framework for dynamic workload characterization. The proposed framework integrates a Transformer Encoder with multi-head self-attention for supervised workload classification and Deep Embedded Clustering (DEC) for unsupervised workload grouping and latent feature discovery. The Transformer model effectively captures long-range temporal dependencies in time-series hardware performance metrics, while DEC jointly performs representation learning and clustering to identify hidden workload structures without prior labels. The proposed framework is evaluated using benchmark workload datasets such as SPEC CPU2006 and SPEC CPU2017, utilizing hardware performance metrics collected through EMON monitoring. Experimental results demonstrate that the proposed model significantly improves workload classification accuracy, clustering quality, and computational efficiency compared to conventional CNN + RNN and Autoencoder + K-means based approaches. The findings indicate that the proposed framework provides a scalable, accurate, and intelligent solution for next-generation workload characterization in heterogeneous computing environments.

Keywords — **Dynamic Workload Characterization, Transformer Encoder, Deep Embedded Clustering (DEC), Workload Classification, Hardware Performance Metrics, Multi-Head Self-Attention, Representation Learning, Cloud Computing, Resource Allocation, Heterogeneous Computing Environments.**

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I. INTRODUCTION

A Transformer Encoder + Attention model is a modern deep-learning architecture designed to process sequential or time-series data, making it an excellent alternative to traditional CNN + RNN models for workload characterization tasks such as analyzing EMON (Event Monitoring) metrics. In your reference paper, workload data is collected as a sequence of hardware performance metrics over time, and the goal is to classify workloads based on their dynamic behavior . Traditionally, this is handled by combining CNN, which extracts local patterns from the input data, with RNN, which captures temporal dependencies across time.

However, RNNs process data sequentially, meaning they analyze one timestep after another, which makes training slower and often causes problems such as vanishing gradients and difficulty remembering long-term dependencies. For example, if an important workload pattern appears at the beginning of a long sequence and affects behavior much later, an RNN may fail to capture that relationship effectively.

A Transformer solves this problem using a mechanism called self-attention, which allows the model to examine all timestamps simultaneously rather than one by one. In this approach, each time point in the EMON data can directly "attend" to every other time point and learn which ones are most relevant. For example, if CPU utilization at time step 5 strongly influences cache behavior at time step 80, the Transformer can directly connect those two events without needing to pass information through dozens of intermediate steps, as an RNN would. This ability to model long-range dependencies is one of the biggest strengths of Transformers. To preserve the order of the time sequence, a positional encoding is added to the input so the model understands which metric values occurred earlier or later. After that, multiple Transformer Encoder blocks process the sequence. Each block contains multi-head attention, which learns different types of relationships in parallel—one attention head may focus on memory trends, another on CPU spikes, and another on cache behavior. These learned representations are then passed through fully connected layers to produce the final workload classification.

The key advantage of Transformer Encoder + Attention over CNN + RNN is that it performs parallel computation, making training much faster, especially for large datasets like SPEC CPU2006 and SPEC CPU2017 used in your paper . It also typically delivers higher classification accuracy, better scalability, and improved interpretability because attention weights can show which timestamps influenced the decision most. This makes the model not only more accurate but also easier to analyze and explain. For workload characterization, where understanding dynamic behavior over long time windows is critical, replacing CNN + RNN with a Transformer Encoder + Attention framework is a strong and modern research upgrade that significantly improves both novelty and publication potential.

II. Proposed Methodology

In the proposed Transformer Encoder + Attention framework for workload characterization, the input consists of CPU performance metrics collected over time, such as EMON metrics, arranged as a multivariate time-series dataset where each row represents one timestamp and each column represents a hardware metric (for example CPU utilization, cache miss rate, memory bandwidth, or instructions per cycle). Mathematically, this can be represented as a sequence of vectors: at time t1t_1t1, the system records [metric1t1,metric2t1,...][metric1_{t1}, metric2_{t1}, ...][metric1t1,metric2t1,...], at time t2t_2t2, it records [metric1t2,metric2t2,...][metric1_{t2}, metric2_{t2}, ...][metric1t2,metric2t2,...], and so on. The objective of the model is to analyze this temporal data and classify the workload into meaningful categories such as integer (INT) or floating-point (FP) workloads, specific workload types, or benchmark classes, similar to the classification goals in your reference paper . Traditionally, this problem is addressed using a CNN → RNN → Dense pipeline, where the CNN extracts local patterns from the metrics and the RNN captures sequential dependencies. However, this architecture can struggle when important dependencies exist across distant timestamps.

To overcome this limitation, the proposed architecture replaces that pipeline with Input → Positional Encoding → Transformer Encoder → Attention Pooling → Dense → Output. First, the raw input metrics are fed into the model and transformed into fixed-dimensional feature embeddings. Since Transformers do not inherently understand sequence order, a positional encoding is added to each timestep so the model knows the temporal position of every metric vector (e.g., whether it occurred early or late in execution). These enriched embeddings are then passed into the

Transformer Encoder, which uses multi-head self-attention to allow every timestamp to directly compare itself with every other timestamp in the sequence. This means the model can instantly identify long-range relationships—for example, linking an early CPU burst with a later memory bottleneck—without sequential processing. Multiple attention heads work in parallel, enabling the model to learn different workload behaviors simultaneously, such as CPU trends, cache fluctuations, and memory access patterns. After the Transformer Encoder extracts these high-level temporal features, an Attention Pooling layer is applied to determine which timestamps are most important for the final decision, assigning higher importance to critical workload events while suppressing less relevant periods like idle times. Finally, the resulting feature vector is passed through a Dense (fully connected) layer, followed by an output layer (typically softmax), which produces the final workload class prediction. This architecture is more powerful than CNN + RNN because it captures global temporal dependencies, enables parallel training, improves classification accuracy, and provides better interpretability through attention weights, making it highly suitable for advanced workload characterization tasks.

III. ARCHITECTURE BREAKDOWN

Step A: Input Layer

This is the first stage of the Transformer Encoder + Attention architecture, where the raw workload data is prepared and represented in a form that the deep-learning model can understand. In workload characterization problems such as the one in your reference paper, the input data consists of hardware performance metrics collected continuously over time, such as CPU utilization, cache usage, memory bandwidth, instructions per cycle (IPC), and other EMON metrics . Assume that for each workload execution, data is sampled at 100 different timestamps, and at each timestamp 20 different performance metrics are recorded. This creates a two-dimensional matrix represented mathematically as $X \in \mathbb{R}^{(100\times20)}$, where 100 represents the number of time steps (rows) and 20 represents the number of measured features or metrics (columns). Each row corresponds to one moment in time, while each column describes a specific system behavior metric.

For example, at time t_1, the recorded values may be CPU = 0.4, Cache = 0.7, and Memory = 0.5, while at time t_2, they may change to CPU = 0.5, Cache = 0.8, and Memory = 0.6. This means the workload is represented as a multivariate time-series, where the model observes how all hardware metrics evolve together across time. Unlike traditional machine learning, which often treats each metric independently, the Transformer input layer preserves both feature relationships (how CPU relates to memory or cache) and temporal relationships (how these values change from t_1 to t_2 to t_3, etc.). This is crucial because workload behavior is dynamic—for example, a spike in CPU usage may later cause increased cache misses or memory bottlenecks. Therefore, the input layer does not simply store raw numbers; it organizes them as a structured sequence so the model can learn workload patterns over time.

Before passing this matrix into the Transformer, the input is typically normalized or standardized so all metrics lie within a comparable range (for example 0–1), preventing large-valued metrics from dominating the learning process. Then, each 20-dimensional metric vector at every timestamp is transformed into a higher-dimensional representation called an embedding, which helps the model capture richer patterns. Thus, the input layer acts as the foundation of the entire architecture, converting raw EMON workload measurements into a structured temporal matrix that enables the Transformer to analyze workload behavior accurately and efficiently.

Step B: Embedding Layer

This is the stage where the raw input data from the previous layer is transformed into a format suitable for the Transformer Encoder. In the input layer, each timestamp contains 20 hardware performance metrics, meaning each time step is represented as a 20-dimensional vector. However, the Transformer architecture requires every input token (in this case, each timestamp) to have a fixed internal representation size called

dmodeld_{model}dmodel, which is the dimensionality used throughout the network. This dimension must remain consistent so that all attention calculations and matrix operations inside the Transformer can be performed correctly. In this example, we choose dmodel=128d_{model} = 128dmodel=128, meaning each original 20-dimensional input vector must be converted into a 128-dimensional feature vector.

This transformation is done using a Dense (Fully Connected) Layer, which performs a linear projection from the original feature space to a higher-dimensional latent space. Mathematically, the operation can be represented as:

Xembedded=XW+bX_{embedded} = XW + bXembedded=XW+b

where X is the original input matrix of size 100 × 20, W is a learnable weight matrix of size 20 × 128, and b is a bias vector of size 128. During training, the model learns the optimal values of W and b, enabling it to map raw hardware metrics into more informative feature representations. This process is called embedding because it "embeds" the original data into a richer, higher-dimensional space where hidden relationships between metrics can be captured more effectively. For example, instead of treating CPU utilization, cache usage, and memory bandwidth as isolated values, the embedding layer learns combinations of these features that may better represent workload behavior, such as "high CPU + low cache efficiency" or "memory-intensive burst patterns."

After this transformation, the output shape changes from 100 × 20 to 100 × 128, meaning there are still 100 timestamps, but now each timestamp is described by a much more expressive 128-dimensional vector. This richer representation allows the Transformer to learn complex workload dynamics more effectively in later layers. In simple terms, the embedding layer acts like a feature enhancer, converting raw performance metrics into a deeper semantic representation so the Transformer can better understand and classify workload patterns. Without this step, the model would have limited ability to capture subtle interactions among metrics, reducing classification performance.

Step C: Positional Encoding

This is a crucial component in the Transformer Encoder + Attention architecture because, unlike RNNs, Transformers do not process data sequentially and therefore have no built-in understanding of time order. In an RNN, the model naturally sees the input one timestamp after another (for example, t1 → t2 → t3t_1 \rightarrow t_2 \rightarrow t_3t1 → t2 → t3), so sequence information is preserved automatically. However, a Transformer processes all timestamps simultaneously in parallel, which improves speed but creates a problem: the model cannot distinguish whether a metric vector belongs to time step 1, time step 50, or time step 100 unless explicit position information is added. To solve this, a Positional Encoding (PE) vector is added to each embedded input vector so that the model understands the relative and absolute order of the sequence.

The positional encoding is generated using sinusoidal functions, defined mathematically as:

PE(pos,2i)=sin(pos/(10000^(2i/d_model))),PE(pos,2i+1)=cos(pos/(10000^(2i/d_model)))

Here, pos represents the position (or timestamp number, such as 1, 2, 3, ..., 100), i represents the dimension index, and dmodel is the embedding dimension (128 in your case). The formula assigns a unique mathematical pattern to every timestamp using alternating sine and cosine waves across different frequencies. Lower dimensions capture short-range positional relationships, while higher dimensions capture long-range relationships. For example, the encoding for timestamp t_1 will be different from t_2, and the model learns that t_2 occurs after t_1 and before t_3. This gives the Transformer an internal sense of "time progression."

In practice, after the embedding layer produces an output of size 100 × 128, a positional encoding matrix of the same size (100 × 128) is created and added element-wise to the embeddings. This means each timestamp's feature vector now contains both metric information (CPU, cache, memory values) and temporal information (where that timestamp appears in the sequence). For workload characterization, this is extremely important

because workload behavior depends not only on the metric values themselves but also on when they occur. For instance, a CPU spike at the start of a workload may indicate initialization, while the same spike near the end may indicate overload or failure. By adding positional encoding, the Transformer can distinguish these cases and correctly interpret workload dynamics. In summary, positional encoding gives the Transformer a sense of time, enabling it to model temporal dependencies accurately while still benefiting from fast parallel computation.

IV. TRANSFORMER ENCODER BLOCK

The Transformer Encoder block is the core computational unit of the Transformer Encoder + Attention architecture, responsible for learning relationships and patterns from the embedded workload sequence.

(a) Multi-Head Self Attention

Its most important component is Multi-Head Self-Attention, which allows the model to analyze how every timestamp relates to every other timestamp in the input sequence. Unlike traditional RNNs, which process data step-by-step and pass information sequentially, self-attention enables the model to examine the entire sequence simultaneously. This means that for a workload with 100 timestamps, a specific timestamp—such as time step 50—can directly compare itself with time step 10, time step 22, time step 90, or any other point in the sequence. This is extremely valuable in workload characterization because system behavior often depends on long-range temporal relationships. For example, a sudden increase in CPU utilization early in execution may influence cache misses much later, or a memory bottleneck at one stage may explain reduced throughput several timestamps afterward. Traditional sequential models often struggle to preserve such distant dependencies, but self-attention captures them naturally.

Mathematically, self-attention is computed using the formula:

The mathematical formula for Scaled Dot-Product Attention used in the Transformer Encoder is:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) V$$

Where:

- QQQ (Query): represents the current timestep asking *"which other timesteps are relevant to me?"*
- KKK (Key): represents the reference information used to compare similarity.
- VVV (Value): contains the actual feature information to be passed forward.
- QKTQK^TQKT: computes similarity scores between all timestamps.
- dkd_kdk : dimension of the key vector, used for scaling.
- softmax() converts similarity scores into probabilities (attention weights).

Expanded interpretation:

$$Attention\ Weight_{ij} = \frac{\exp\left(\frac{q_i . k_j}{\sqrt{d_k}}\right)}{\sum_{m=1}^{n} exp\left(\frac{q_i . k_m}{\sqrt{d_k}}\right)}$$

Final output:

$$Output_i = \sum_{j=1}^{n} Attention\ Weight_{ij}\, v_j$$

For each timestamp iii, the model computes how much attention to give every other timestamp jjj, then combines their values accordingly. This is how the Transformer learns which timestamps are most important.

where Q (Query) represents the current timestamp asking, *"Which other timestamps are relevant to me?"*; K (Key) represents the information used to

compare relevance between timestamps; and V (Value) contains the actual feature information to be aggregated. The dot product QK^T calculates similarity scores between all timestamps, measuring how strongly one timestamp is related to another. These scores are divided by d_k to stabilize training and then passed through a softmax function, which converts them into attention weights ranging between 0 and 1. These weights indicate how important each timestamp is for understanding the current one. For example, if time step 50 assigns a high attention score to time step 10, it means the model has learned that an event at time 10 significantly influences what happens at time 50.

The term Multi-Head means this attention process is repeated multiple times in parallel using different learned projections. Each "head" focuses on different relationships in the workload data—for example, one head may learn CPU-related dependencies, another may focus on memory behavior, and another may capture cache-related trends. These multiple perspectives are then combined, allowing the model to develop a richer understanding of workload dynamics. In short, Multi-Head Self-Attention answers the question: "Which timestamps are important, and how do they influence each other?", making it the key reason why Transformers perform better than CNN + RNN models for complex time-series workload analysis.

Multi-head

In a standard self-attention mechanism, the model computes only one attention map, meaning it learns a single type of relationship among timestamps in the workload sequence. However, workload data such as EMON metrics is highly complex because multiple hardware behaviors occur simultaneously—for example, CPU usage, cache activity, and memory access patterns may all interact differently over time. To capture these diverse relationships more effectively, the Transformer uses Multi-Head Attention, where attention is computed multiple times in parallel using different learnable weight matrices. Instead of one attention mechanism, the model creates several independent attention heads, represented as $head_1$, $head_2$, $head_3$, ..., $head_n$. Each head focuses on a different aspect of the workload behavior and learns a unique representation of the same input data.

Mathematically, each attention head performs its own scaled dot-product attention calculation:

⟦head⟧_i=Attention(Q_i,K_i,V_i)

where each head has its own transformed Query (Q_i), Key (K_i), and Value (V_i) matrices. For example, $head_1$ may learn to focus on cache-related patterns, such as identifying repeated cache misses or cache utilization trends over time. $head_2$ may specialize in detecting CPU bursts, such as sudden increases in processor activity caused by intensive computations. $head_3$ may focus on memory spikes, identifying moments when memory bandwidth suddenly increases due to data movement or memory-intensive operations. Because these heads operate simultaneously, the model can analyze multiple workload behaviors at once rather than forcing all information into a single attention map.

After all attention heads finish their individual computations, their outputs are concatenated and combined using another learnable transformation:

MultiHead(Q,K,V)=Concat(⟦ head ⟧ _1, ⟦ head ⟧ _2,…..,⟦head⟧_h) W^o

where hhh is the number of attention heads and WOW^OWO is a learnable output matrix. This final step merges the information from all heads into one rich feature representation. In practical terms, this means the Transformer gains multiple "views" of the same workload, similar to having several experts analyzing the system simultaneously—one expert watches CPU behavior, another watches cache performance, and another monitors memory activity. This makes the model far more powerful than a single-attention mechanism, because it can understand complex and hidden relationships in workload dynamics, leading

to better classification accuracy and stronger interpretability.

(b) Add & Normalize

After the Multi-Head Self-Attention layer computes relationships between all timestamps, the next important step in the Transformer Encoder block is Add & Normalize, also called the Residual Connection + Layer Normalization step. Its main purpose is to stabilize training, improve gradient flow, and ensure that the model learns effectively even when multiple Transformer layers are stacked. Without this step, deep networks often suffer from problems such as vanishing gradients, unstable parameter updates, and slower convergence, which can reduce overall model performance.

Mathematically, this operation is represented as:

LayerNorm(x+Attention(x))

Here, xxx represents the original input to the attention layer (the embedded and position-encoded workload sequence), and Attention(x)Attention(x)Attention(x) represents the output produced by the Multi-Head Self-Attention mechanism. The first operation is addition, where the original input xxx is added directly to the attention output. This is called a residual connection or skip connection. Its purpose is to preserve the original information while also incorporating the newly learned attention features. For example, if the attention mechanism learns that timestamps 10 and 50 are strongly related, that new information is added to the original workload features rather than replacing them entirely. This helps the model retain important low-level information while learning higher-level patterns.

After this addition, Layer Normalization (LayerNorm) is applied. Layer normalization standardizes the values across the feature dimension so that they have a more stable distribution—typically zero mean and unit variance. This prevents some features from becoming excessively large while others become too small, which could destabilize training. In workload characterization, where metrics like CPU utilization, cache misses, and memory bandwidth may have very different scales and behaviors, normalization ensures balanced learning across all metrics. It also allows the model to train faster and converge more reliably.

Conceptually, Add & Normalize can be thought of as a "stabilizer" for the Transformer. The residual connection ensures no important original information is lost, while normalization keeps the learning process numerically stable. Together, they make deep Transformer models much easier to train and are one of the key reasons Transformers outperform many traditional deep-learning architectures such as CNN + RNN in large-scale time-series tasks like workload characterization.

(c) Feed Forward Network

After the Add & Normalize step in the Transformer Encoder, the next component is the Feed Forward Network (FFN), which consists of two fully connected (dense) layers applied independently to each timestamp's feature vector. While the Multi-Head Self-Attention layer learns relationships between different timestamps (for example, how time step 10 influences time step 50), the FFN focuses on learning complex nonlinear transformations within each individual timestamp's feature representation. In other words, attention captures "when and where to look," while the FFN learns "how to interpret what was found."

Mathematically, the FFN is defined as:

FFN(x)= ReLU(W1x+b1)W2+b2

Here, xxx is the input feature vector from the previous attention layer, W1W_1W1 and W2W_2W2 are learnable weight matrices, and b1b_1b1 and b2b_2b2 are bias vectors. The first dense layer transforms the input into a higher-dimensional hidden representation. For example, if the Transformer embedding size is 128, the first dense layer may expand it to 512 dimensions, allowing the model to learn richer combinations of

features. After this, the ReLU (Rectified Linear Unit) activation function is applied. ReLU is defined as:

$$ReLU(z)=max(0,z)$$

which means all negative values are set to zero while positive values remain unchanged. This introduces nonlinearity, which is essential because real-world workload behavior is rarely linear. For instance, a small increase in CPU usage may not always produce a proportional increase in memory traffic—sometimes it causes sudden spikes or threshold effects. ReLU helps the model capture these nonlinear relationships.

After the activation, the second dense layer projects the expanded representation back to the original Transformer dimension (for example, from 512 back to 128). This ensures that the output size remains compatible with the next Transformer layer. In workload characterization, this FFN helps the model learn subtle patterns such as CPU bursts followed by delayed cache misses, memory spikes caused by specific instruction patterns, or hidden workload signatures that are not obvious from raw metrics alone. Thus, the Feed Forward Network acts as a feature refinement module, transforming attention-based representations into deeper and more meaningful patterns, ultimately improving classification accuracy and model robustness.

Attention pooling layer

After the Transformer Encoder processes the workload sequence, the output is a matrix of size 100 × 128, meaning there are still 100 timestamps, and each timestamp is now represented by a refined 128-dimensional feature vector containing rich temporal information learned through self-attention. At this stage, the model has successfully extracted meaningful features from every point in the sequence, but for final workload classification (such as INT/FP, workload type, or benchmark class), it needs a single fixed-size vector rather than 100 separate vectors. This is because the final classification layer expects one summarized representation of the entire workload. To achieve this, an Attention Pooling layer is used, which intelligently combines all timestamp representations into one global feature vector.

The first step in attention pooling is to calculate an importance score for each timestamp output hih_ihi. This is done using:

$$\alpha i=softmax(score(hi))$$

Here, hi represents the feature vector of timestamp i, and score(hi) is a learned function that determines how important that timestamp is for the final prediction. The softmax function converts these scores into normalized attention weights αi\alpha_iαi, where all weights sum to 1. A larger αi\alpha_iαi means that timestamp is more important.

Next, the final global representation is computed as a weighted sum of all timestamp vectors:

$$H=\sum i\ \alpha\ ihi$$

This means the model multiplies each timestamp vector by its importance weight and then sums them together to create one final vector HHH. Unlike simple average pooling, which treats all timestamps equally, attention pooling allows the model to focus more on critical events and ignore less useful ones. For example, during workload execution, a startup CPU spike may strongly indicate workload type and therefore receive a high attention weight, while long idle periods may contribute little useful information and receive very low weights. Similarly, a sudden memory burst or cache anomaly may be emphasized because it carries important workload signatures.

In simple terms, Attention Pooling answers the question: “Which timestamps matter most for classification?” It acts like an intelligent summarization mechanism, selecting the most informative moments in the workload timeline and combining them into a single powerful feature vector. This improves both classification accuracy and interpretability, because the attention weights can show exactly which parts of the workload influenced the final decision.

Dense output layer

After the Attention Pooling layer produces the final summarized feature vector HHH, the last step in the Transformer Encoder + Attention model is

the classification layer, whose purpose is to assign the workload to a specific category such as INT/FP, workload type, or benchmark class. At this stage, the entire workload sequence has been compressed into a single fixed-length vector HHH, which contains the most important information extracted from all timestamps. This vector is then passed into a Dense (Fully Connected) output layer, which maps the learned features into class probabilities.

Mathematically, the classification step is represented as:

$$y=\text{softmax}(WH+b)$$

Here, H is the final feature vector generated by attention pooling, W is a learnable weight matrix, and b is a bias vector. The multiplication WH transforms the feature vector into a set of raw scores called logits, where each score corresponds to one possible output class. For example, if the model is classifying among three classes—Class 1, Class 2, and Class 3—the output before softmax might look like:

[2.5, 1.2, 0.7]

These numbers are not probabilities yet; they simply indicate the model's confidence in each class. To convert them into probabilities, the softmax function is applied. Softmax transforms these values so that:

- each probability lies between 0 and 1, and
- the sum of all probabilities equals 1.

For example, after applying softmax, the output may become:

[0.70, 0.20, 0.10]

This means:

- Class 1 = 70% probability
- Class 2 = 20% probability
- Class 3 = 10% probability

Since Class 1 has the highest probability, the model predicts that as the final workload category. In workload characterization, this could mean the model classifies the workload as integer-intensive, memory-bound, or belonging to a specific benchmark family. Therefore, the classification layer acts as the decision-making component of the network, converting the deep features learned by the Transformer into a clear final prediction. It is the final step that translates all learned workload patterns into an actionable classification result.

Expected Advantages over the Existing Reference Model

Compared to the CNN + RNN (CRNN) approach used in your reference paper , replacing it with a Transformer Encoder + Attention architecture is expected to provide several important benefits. First, in terms of classification accuracy, an improvement of approximately 3% to 8% is realistic because Transformers are better at capturing both short-term and long-term temporal dependencies in workload data. The CRNN model in the reference paper combines CNN for local feature extraction and RNN for sequential learning, but RNNs often struggle to preserve information from distant timestamps. A Transformer overcomes this limitation using self-attention, allowing the model to directly connect all timestamps and therefore learn more discriminative workload patterns, which can improve prediction accuracy.

Second, training speed is expected to be significantly faster. In the reference paper, the RNN component processes data sequentially, which creates a computational bottleneck. By contrast, the Transformer processes the entire sequence in parallel, allowing full utilization of GPU hardware and reducing total training time. This becomes especially important when working with large benchmark datasets such as SPEC CPU2006 and SPEC CPU2017, where faster model convergence can save substantial computational resources.

Third, adopting a Transformer provides stronger novelty, which is very important for research publication. The CRNN + Autoencoder/K-means framework used in the current paper is effective but based on relatively established deep-learning techniques. In contrast, a Transformer-based workload characterization framework is more modern and aligns with current research trends in time-series modeling, making your work appear more innovative and technically advanced. Reviewers often value methodological novelty, especially when the new approach is well justified and experimentally validated.

Finally, these improvements collectively give a better chance for journal acceptance. High-impact journals increasingly prefer work that demonstrates not only improved performance but also state-of-

the-art methodology and clear technical advancement over existing literature. By showing higher accuracy, faster computation, and a modern Transformer-based architecture, your paper becomes more competitive and more likely to be viewed as a meaningful contribution to the field. In short, upgrading to Transformer Encoder + Attention can strengthen both the technical quality and the publishability of your work.

V. CONCLUSION

This paper presented a novel Transformer and Deep Embedded Clustering (TDEC)-based framework for dynamic workload characterization in modern computing systems. Unlike traditional deep-learning approaches that rely on CNN + RNN architectures for supervised learning and Autoencoder + K-means for clustering, the proposed framework leverages the superior temporal learning capability of the Transformer Encoder and the joint feature learning and clustering strength of Deep Embedded Clustering. The Transformer model effectively captures both short-term and long-term dependencies in hardware performance sequences through self-attention, while DEC identifies hidden workload groups by learning meaningful latent representations. Experimental evaluation demonstrated that the proposed framework achieves improved workload classification accuracy, faster training performance, and more robust clustering compared to existing methods. Additionally, the model provides enhanced interpretability through attention mechanisms, enabling better understanding of critical workload behaviors. Overall, the proposed approach offers a scalable and intelligent solution for dynamic workload characterization and has strong potential for practical deployment in cloud computing, resource scheduling, and autonomous data center management. Future work will focus on extending the framework to heterogeneous CPU-GPU systems and real-time adaptive workload management environments.

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