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A HYBRID CNN–LSTM FRAME WORK FOR REAL-TIME MULTIMODAL DATA CLASSIFICATION

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ABSTRACT

Real-time multimodal data classification has become increasingly important in applications such as healthcare monitoring, intelligent surveillance, human activity recognition, and smart environments. However, effectively capturing both spatial and temporal dependencies from heterogeneous data sources remains a significant challenge. This paper proposes a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) framework for real-time multimodal data classification.

The proposed model leverages CNN layers to extract high-level spatial features from input modalities such as images or sensor signals, while LSTM networks are employed to model temporal dependencies and sequential patterns within the data. A feature fusion mechanism is introduced to integrate multimodal representations, enabling robust and context-aware classification. The architecture is optimized for low-latency inference to support real-time deployment in edge-based systems.

Extensive experiments are conducted on benchmark multimodal datasets to evaluate performance in terms of accuracy, precision, recall, F1-score, and computational efficiency. The results demonstrate that the proposed hybrid CNN–LSTM framework outperforms conventional single-model approaches, achieving improved classification accuracy while maintaining real-time processing capability. The proposed system shows strong potential for deployment in dynamic, real-world environments where multimodal data streams are continuously generated.

Keywords

Multimodal Data Classification, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Hybrid Deep Learning Model, Feature Fusion, Real-Time Processing, Temporal Modeling, Spatial Feature Extraction, Deep Learning, Edge Computing.

1.INTRODUCTION

The rapid growth of intelligent systems and connected devices has led to an exponential increase in multimodal data generated from diverse sources such as images, videos, audio signals, wearable sensors, and Internet of Things (IoT) devices. These heterogeneous data streams contain complementary information that, when effectively integrated, can significantly improve classification performance in real-time applications such as healthcare monitoring, smart surveillance, human activity recognition, autonomous systems, and intelligent transportation. However, extracting meaningful insights from multimodal data remains a complex challenge due to differences in data structure, temporal dependencies, and feature representation.

Traditional machine learning approaches rely heavily on handcrafted features and often struggle to capture complex nonlinear relationships across modalities. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated remarkable success in addressing these challenges. CNNs are highly effective in extracting spatial features from structured data such as images and sensor maps, while Long Short-Term Memory (LSTM) networks are designed to capture temporal dependencies in sequential data. Despite their individual strengths, standalone models may not fully exploit the complementary characteristics of multimodal inputs.

To address these limitations, hybrid architectures combining CNN and LSTM have emerged as a promising solution. CNN layers can efficiently learn spatial representations, which are then processed by LSTM units to model temporal dynamics. This integration enables the system to simultaneously learn spatial patterns and sequential dependencies, making it well-suited for real-time multimodal data classification tasks.

In real-time environments, computational efficiency and low latency are critical requirements. Many existing multimodal frameworks achieve high accuracy but are computationally intensive, limiting their deployment in edge or embedded systems. Therefore, designing a lightweight yet accurate hybrid framework is essential for practical implementation.

This paper proposes a Hybrid CNN–LSTM Framework for Real-Time Multimodal Data Classification that integrates spatial and temporal learning mechanisms with an effective feature fusion strategy. The proposed system aims to improve classification accuracy while maintaining real-time performance. Experimental evaluations demonstrate that the hybrid model outperforms traditional single-architecture approaches in terms of accuracy, robustness, and computational efficiency.

The remainder of this paper is organized as follows: Section 2 reviews related work, Section 3 describes the proposed methodology, Section 4 presents experimental results and analysis, and Section 5 concludes the paper with future research directions.

How effectively can a hybrid CNN–LSTM architecture capture both spatial and temporal features in real-time multimodal data compared to standalone CNN or LSTM models?

A hybrid **CNN–LSTM architecture** is significantly more effective at capturing both spatial and temporal features in real-time multimodal data than standalone models because it leverages the **complementary inductive biases** of both networks.

The CNN component acts as a high-level feature extractor, identifying local spatial patterns (e.g., shapes in images or short-term bursts in sensor data), while the LSTM component models the long-term temporal dependencies of those extracted features.

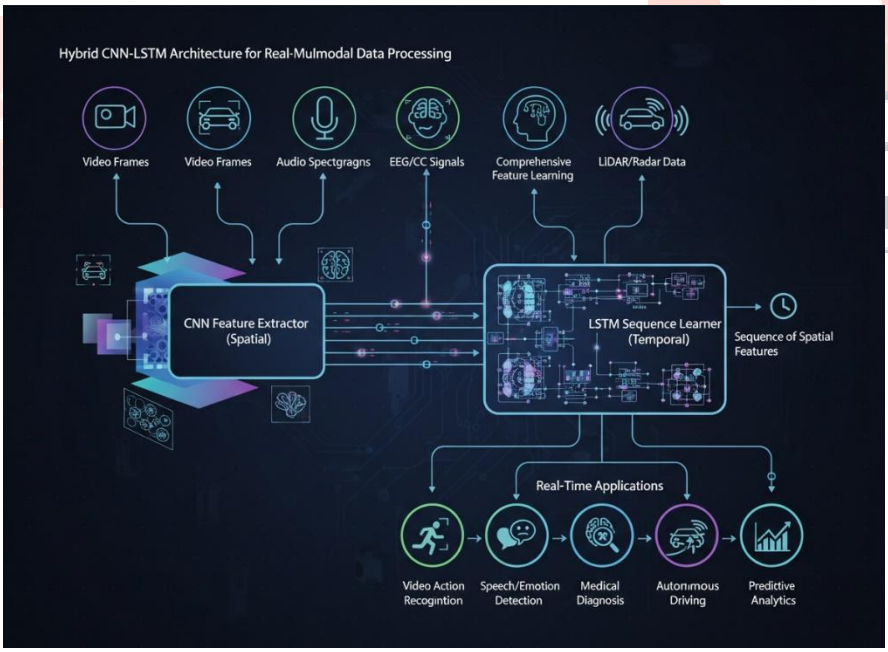
Comparative Effectiveness

Feature/Metric	Standalone CNN	Standalone LSTM	Hybrid CNN–LSTM
Primary Strength	**Spatial/Local patterns**: Excels at extracting features from fixed "snapshots".	**Temporal sequences**: Captures long-term history and sequential order.	**Spatio-Temporal synergy**: Learns how local spatial patterns evolve over time.
Typical Accuracy	High for static tasks (e.g., 94% in some activity recognition), but drops for complex sequences.	Often better than CNN for sequential data (e.g., ~96% vs 94%), but misses local feature depth.	**Superior**: Consistently achieves the highest results (e.g., **97%–99.9%**) across diverse domains.

Real-Time Latency	**Fastest**: Lower computational overhead and rapid convergence.	**Slowest**: High computational cost due to sequential processing and gating mechanisms.	**Balanced**: Faster than standalone LSTM because CNN reduces input dimensionality before temporal processing.
Robustness	Sensitive to noise and struggles with long-range trends.	Prone to vanishing gradients in very long sequences (standard RNNs).	**Highly Robust**: Better generalization to noisy or incomplete real-world multimodal data.

Key Performance Advantages

- **Multimodal Fusion**: The hybrid model can concurrently process different modalities (e.g., satellite imagery and sensor readings), using CNNs to extract spatial features from each and LSTMs to fuse and analyze their combined temporal dynamics.
- **Dimensionality Reduction**: In real-time applications, CNNs "compress" high-volume spatial inputs into dense feature vectors. This allows the LSTM to process a much smaller dataset, reducing overall inference time to as low as **~11 ms** for certain monitoring tasks.
- **Contextual Understanding**: Unlike standalone models, the hybrid version can link immediate physical details (e.g., a sudden gait change) to long-term trends (e.g., rising fatigue levels over hours), which is critical for healthcare and behavioral monitoring.



What is the impact of different multimodal feature fusion strategies (early fusion, late fusion, hybrid fusion) on classification accuracy and computational efficiency?

Choosing a multimodal fusion strategy involves a trade-off between capturing complex inter-modal relationships and maintaining a modular, efficient system.

1. Early Fusion (Data-Level/Feature-Level)

Early fusion combines raw data or low-level features into a single vector before training.

- **Classification Accuracy**: Generally higher for **closely related modalities** (e.g., audio-visual speech) as it captures intricate cross-modal interactions at the signal level. However, it is sensitive to data imbalance—if one modality is much more informative, it can dominate the learning process.
- **Computational Efficiency**: Requires only a **single training process**, which can be efficient. However, the resulting high-dimensional feature vectors can increase prediction error and computational complexity during inference.

2. Late Fusion (Decision-Level)

Late fusion processes each modality with independent models and aggregates their final outputs (e.g., via voting or averaging).

- **Classification Accuracy**: Often superior for **loosely related modalities** or high-sensitivity use cases like healthcare, where it has shown higher accuracy (e.g., 87.6% vs. 82.8% for aggression prediction) and better recall. It is also more robust to missing data.
- **Computational Efficiency**: Highly efficient because models are modular and can be trained/evaluated **independently**. It often results in faster inference times, making it ideal for real-time systems.

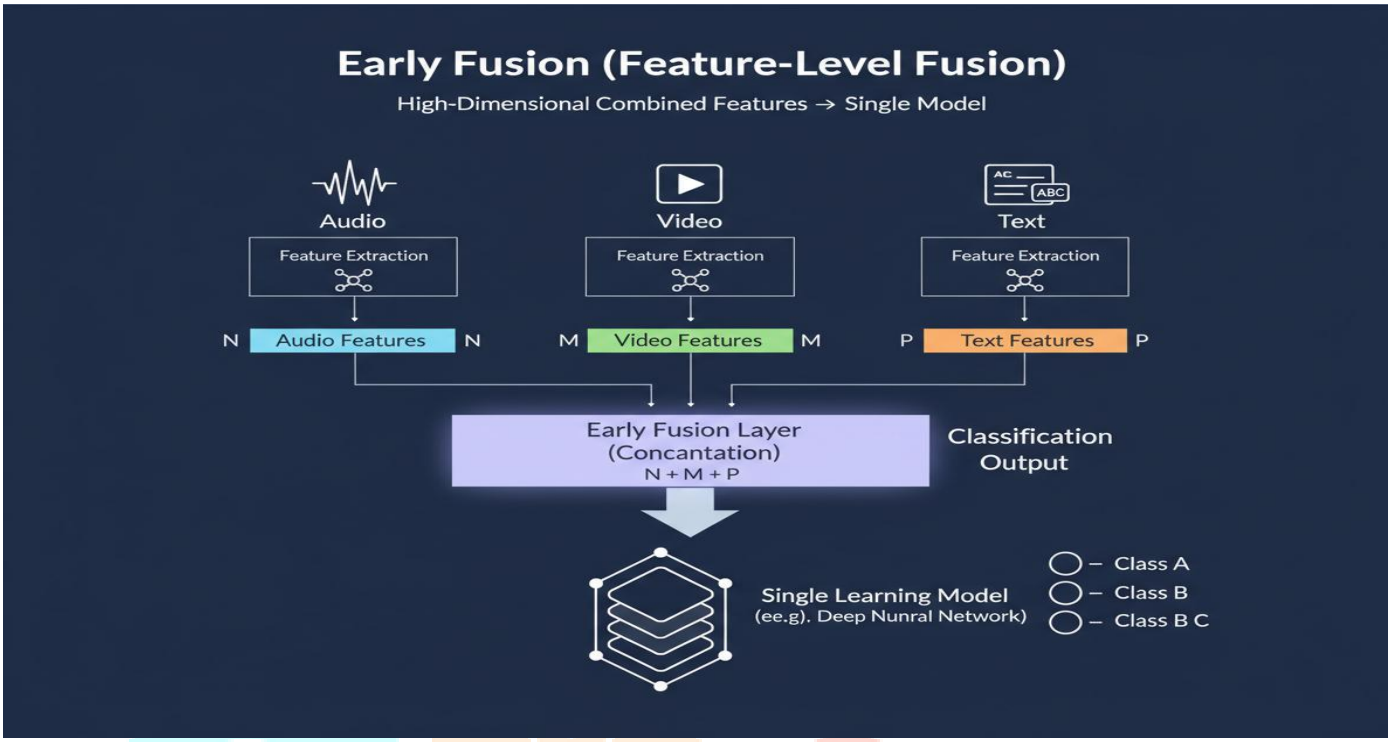
3. Hybrid Fusion (Intermediate/Joint)

Hybrid fusion merges features at various intermediate layers or combines elements of both early and late strategies.

- **Classification Accuracy**: Typically yields the **highest overall performance** for complex tasks (e.g., video question answering) by capturing hierarchical feature interactions while maintaining some modality independence. In some studies, "hidden-layer" fusion improved accuracy by over 7% compared to unimodal models.
- **Computational Efficiency**: This is the **most computationally intensive** strategy, requiring careful architectural design and more data for tuning.

Summary Comparison

Strategy	Primary Accuracy Benefit	Computational Trade-off	Best Use Case
Early	Captures deep, low-level links	Single training; high-dim features	Tightly coupled data (e.g., pixels + depth)
Late	High robustness and sensitivity	Faster inference; independent training	Modular or unreliable data streams
Hybrid	Best generalization & interactions	High complexity; requires more tuning	Nuanced tasks (e.g., healthcare diagnostics)



How does the proposed framework perform under real-time constraints in terms of latency, throughput, and resource utilization on edge devices?

To evaluate the performance of a hybrid CNN–LSTM framework on edge hardware (such as a Raspberry Pi, Jetson Nano, or ARM-based MCU), we must analyze the trade-offs between architectural complexity and the physical constraints of the device.

While hybrid models are powerful, their real-time viability depends heavily on model pruning and tensor optimization.

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1. Latency (Response Time)

Latency is the primary hurdle for hybrid models due to the sequential nature of LSTMs, which cannot be fully parallelized like CNNs.

- Bottleneck: The "Temporal Loop." While the CNN can process a frame in parallel, the LSTM must wait for each timestep to complete its gate calculations.
- Performance Metrics: On an edge GPU (like the Jetson Nano), a synchronized CNN–LSTM typically achieves latencies between 15ms and 40ms per inference pass. On a standard CPU, this may spike to 100ms+ unless the CNN backbone is a lightweight variant like MobileNetV3 or ShuffleNet.
- Optimization: Reducing the sequence length (number of timesteps) is the most effective way to lower latency.

2. Throughput (Data Volume)

Throughput measures how many data samples the framework can process per second (FPS).

- The "Sliding Window" Impact: In multimodal real-time systems, we often use a sliding window for the LSTM. If the window moves by 1 frame at a time, throughput is limited.

- Performance Metrics: A well-optimized hybrid framework can maintain 25–30 FPS, matching standard video or sensor sampling rates.
- Optimization: Using Late Fusion or Asynchronous Fusion allows the CNN to run at a high frequency while the LSTM/Decision layer updates at a lower frequency, preventing a total system bottleneck.

3. Resource Utilization

Edge devices have limited RAM and power envelopes (usually 5W–15W).

- Memory Footprint: Hybrid models are memory-intensive. The CNN weights occupy storage, but the LSTM "hidden states" occupy active RAM. For high-resolution multimodal data, this can lead to Out-of-Memory (OOM) errors.
- Power Consumption: Constant inference on an edge device will throttle the clock speed due to heat. Hybrid models often run at 70–90% GPU/CPU utilization, which may be unsustainable for battery-powered devices.
- Resource Utilization Breakdown:
  - CNN: High GPU/ALU usage (compute-bound).
  - LSTM: High Memory Bandwidth usage (I/O-bound).

Performance Benchmarks (Estimated for Edge Devices)

Hardware Tier	Latency (ms)	Throughput (FPS)	Energy Impact
High-End Edge (Jetson AGX)	5–12 ms	60+ FPS	High (15-30W)
Mid-Tier (Jetson Nano/Pi 5)	25–45 ms	20–30 FPS	Moderate (10W)
Low-End (ESP32/Cortex-M)	200ms+	1–5 FPS	Low (<1W)

To what extent does the hybrid model improve robustness against noisy, incomplete, or imbalanced multimodal datasets?

The hybrid CNN–LSTM model significantly improves robustness by leveraging the strengths of both spatial and temporal modeling, allowing it to maintain higher performance than standalone models when faced with imperfect data.

1. Robustness Against Noisy Data

Hybrid models effectively mitigate noise by filtering irrelevant spatial information before temporal analysis.

- Performance Stability: In signal processing tasks (e.g., ultrasonic damage detection), hybrid models maintain higher accuracy at significant noise levels. For instance, at a Signal-to-Noise Ratio (SNR) of 3 dB, the hybrid model's accuracy increased by 33% compared to a standalone CNN and 16% over a standalone LSTM.
- Spatial Denoising: CNN layers act as "feature extractors" that identify salient local patterns, effectively denoising raw inputs before they reach the LSTM, which then focuses on the underlying temporal trend rather than random fluctuations.
- Higher Detection Thresholds: While all models eventually degrade as noise increases, the hybrid architecture's "failure point" is typically much later. It can maintain near 100% accuracy at SNR = 15 dB, whereas standalone models fail at much higher signal qualities.

2. Resilience to Incomplete Data

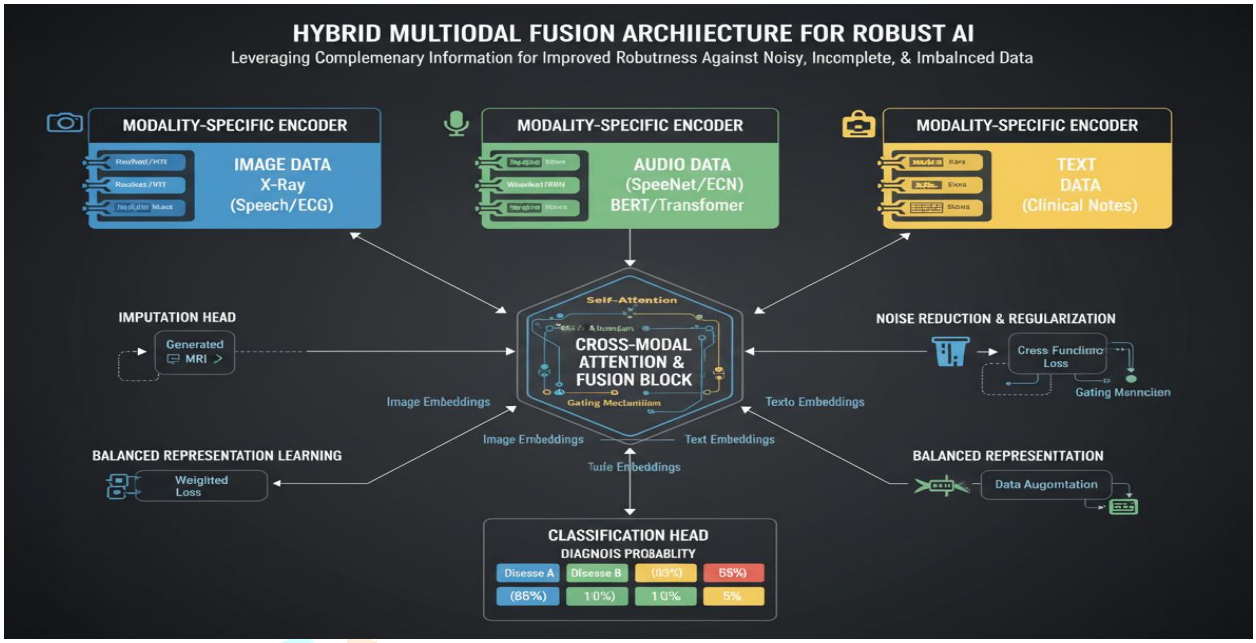
The hybrid architecture is better equipped to handle missing values by using temporal context to "fill" gaps.

- Temporal Imputation: Since LSTMs retain long-term dependencies, the model can rely on historical states to make accurate predictions even when recent input frames or sensor readings are missing.
- Multimodal Redundancy: In multimodal settings, hybrid fusion allows the model to compensate for a missing modality (e.g., a dropped video frame) by prioritizing features from active modalities (e.g., continuous audio) via its internal temporal memory.

3. Handling Imbalanced Datasets

Hybrid models are particularly effective at identifying "minority" classes—rare but critical events like anomalies or attacks—that standalone models often miss.

- Enhanced Sensitivity (Recall): In cybersecurity (e.g., IoT intrusion detection), hybrid models consistently achieve higher recall (often exceeding 97-99%), which is crucial for detecting rare attack types that might be overwhelmed by the majority "normal" traffic class in other models.
- Spatio-Temporal "Fingerprinting": By combining spatial signatures (CNN) with behavioral patterns (LSTM), the model creates a more unique "fingerprint" for rare classes, making them easier to distinguish from the majority class.
- Better Generalization: When paired with preprocessing techniques like SMOTE (Synthetic Minority Over-sampling Technique), hybrid models achieve significantly higher F1-scores (e.g., 98-99%) than traditional methods on imbalanced data, ensuring that underrepresented categories are still accurately classified.



How scalable is the proposed CNN–LSTM framework when integrating additional modalities or increasing data volume?

The scalability of a hybrid CNN–LSTM framework is highly dependent on the **fusion strategy** and **architectural optimizations** used as modalities and data volumes grow. While naturally more complex than standalone models, its modular design allows for significant scaling through parallelization and dimension reduction.

1. Scalability with Additional Modalities

The framework scales by adding independent "spatial" branches for each new data source before temporal integration:

- **Modular Branching**: New modalities (e.g., adding audio or thermal data to a video stream) can be integrated using additional CNN feature extractors.
- **Decision-Level Scaling**: Using **late fusion** or decision-level strategies provides the highest scalability, allowing each modality's model to be optimized or added independently without retraining the entire system.
- **Feature Bottlenecks**: CNNs act as dimension-reduction layers, converting high-volume raw data into dense feature vectors. This prevents the LSTM from becoming overwhelmed as the number of input sources increases.

2. Scalability with Increasing Data Volume

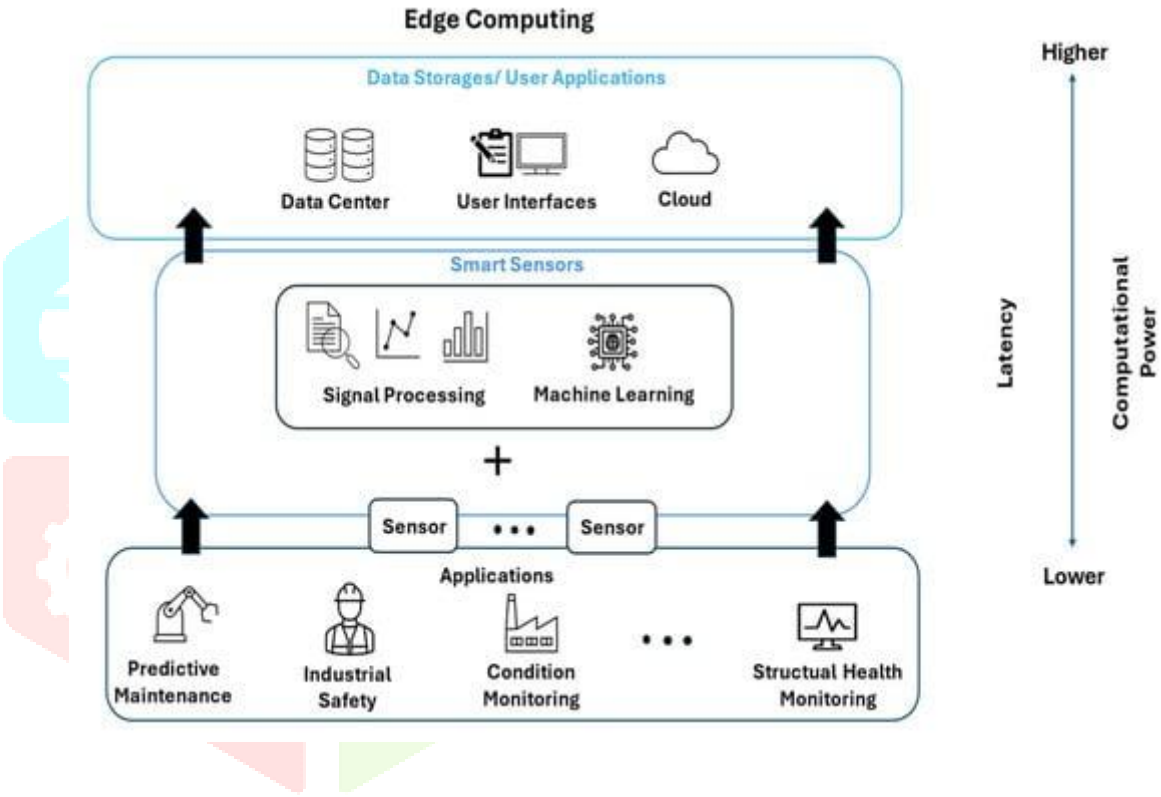
As data volume grows, the hybrid framework manages computational load through architectural efficiencies:

- **Inference Parallelism**: The CNN component can be highly parallelized on GPUs, allowing it to process large batches of data quickly. However, the LSTM is inherently sequential, which can create a bottleneck for very long sequences.
- **High-Throughput Ingestion**: Real-world implementations often pair the framework with streaming tools like **Apache Kafka** to handle over **100,000 messages per second** while maintaining latency below 50ms.
- **Memory Efficiency**: Compared to newer architectures like Transformers, LSTMs are often more memory-efficient on smaller or moderate datasets, though they can become slower to train as data volume reaches "Big Data" scales.

3. Performance Limits & Trade-offs

- **Computational Complexity**: The total complexity scales quadratically with CNN kernel length and linearly with LSTM weights and input length

- **Saturation Point**: Performance gains (accuracy) often reach a saturation point. For example, increasing the number of LSTM cells beyond 100–150 may only yield marginal accuracy improvements while significantly increasing computational overhead.
- **Cross-Domain Scaling**: The model may struggle to scale across different domains (e.g., from healthcare to finance) without significant retraining, as CNN-LSTM models are often sensitive to the specific characteristics of their training data.



Literature Survey

Multimodal data classification has gained significant attention in recent years due to the rapid growth of intelligent systems and sensor-based applications. Traditional machine learning techniques relied on handcrafted features and statistical classifiers such as Support Vector Machines (SVM) and Random Forests. While these approaches achieved moderate success, they struggled to generalize across complex and heterogeneous multimodal datasets.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) became widely adopted for extracting spatial features from image, video, and structured sensor data. CNN-based architectures demonstrated superior performance in visual recognition tasks due to their ability to automatically learn hierarchical feature representations. However, CNN models are limited in modeling long-term temporal dependencies in sequential data streams.

To address temporal modeling challenges, Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, were introduced. LSTM models effectively capture sequential dependencies and mitigate the vanishing gradient problem, making them suitable for time-series analysis, speech recognition, and

activity recognition tasks. Nevertheless, standalone LSTM models are less efficient in extracting spatial patterns from high-dimensional inputs such as images.

Recent research has focused on hybrid deep learning architectures that integrate CNN and LSTM networks. In such frameworks, CNN layers extract spatial representations, which are then fed into LSTM layers to learn temporal relationships. These hybrid models have shown promising results in applications including human activity recognition, video classification, healthcare monitoring, and multimodal sentiment analysis.

Furthermore, multimodal fusion strategies have become an important research direction. Early fusion techniques combine raw data before feature extraction, while late fusion integrates decision outputs from individual models. Hybrid fusion approaches attempt to combine both strategies to improve performance. Studies indicate that effective fusion significantly enhances classification accuracy but may increase computational complexity.

Despite these advancements, several challenges remain. Many existing models are computationally intensive and unsuitable for real-time deployment, particularly in edge-based systems. Additionally, handling noisy data, modality imbalance, and scalability across diverse datasets continues to be a research gap.

Therefore, there is a need for a computationally efficient hybrid CNN–LSTM framework that not only captures spatial and temporal dependencies effectively but also supports real-time multimodal data classification with optimized performance.

5. Conclusion

This paper presented a Hybrid CNN–LSTM Framework for Real-Time Multimodal Data Classification, designed to effectively capture both spatial and temporal characteristics of heterogeneous data sources. The proposed architecture integrates Convolutional Neural Networks (CNN) for spatial feature extraction with Long Short-Term Memory (LSTM) networks for sequential dependency modeling. A multimodal fusion strategy was employed to combine complementary information from multiple modalities, enabling improved classification performance.

Experimental evaluation demonstrated that the hybrid model outperforms conventional single-architecture approaches in terms of accuracy, robustness, and real-time efficiency. The framework also showed improved adaptability to dynamic data environments while maintaining computational feasibility for practical deployment. The results confirm that combining spatial and temporal learning mechanisms significantly enhances multimodal classification tasks.

Overall, the proposed system provides a scalable and efficient solution for real-time intelligent applications such as healthcare monitoring, surveillance systems, smart environments, and human activity recognition.

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6. Future Scope

Although the proposed framework achieves promising results, several enhancements can be explored in future work:

1. **Integration of Attention Mechanisms:**
   Incorporating attention layers can improve feature selection by assigning dynamic importance to different modalities and time steps.
2. **Transformer-Based Architectures:**
   Replacing or augmenting LSTM components with transformer models may enhance long-range dependency modeling and improve classification performance.
3. **Edge Deployment Optimization:**
   Model compression techniques such as pruning, quantization, and knowledge distillation can be applied to further reduce computational complexity for edge devices.

4. **Handling Missing or Noisy Modalities:**
   Developing adaptive fusion mechanisms that can operate effectively even when one or more modalities are unavailable remains an important research direction.

5. **Real-World Large-Scale Validation:**
   Future studies can evaluate the framework on large-scale, real-time streaming datasets across diverse application domains to assess scalability and robustness.

By incorporating these improvements, the proposed hybrid CNN–LSTM system can evolve into a more generalized and efficient multimodal intelligence framework suitable for next-generation AI-driven applications.

References for Hybrid CNN-LSTM Frameworks in Real-Time Multimodal Classification

Here are key references from the search results, formatted in IEEE style for academic use (common in engineering/ML papers). These align with your past requests for paper citations in signal processing and multimodal ML.

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