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Hybrid CNN–Transformer Model for Time-Series Prediction

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Abstract:
Time-series prediction plays a vital role in numerous real-world applications such as energy forecasting, financial analysis, healthcare monitoring, and industrial automation. Traditional statistical and deep learning models often face limitations in capturing both short-term local patterns and long-term temporal dependencies. To address this challenge, this paper proposes a **Hybrid CNN–Transformer model** for accurate time-series forecasting. The Convolutional Neural Network (CNN) component extracts local temporal features, while the Transformer encoder captures long-range dependencies using self-attention mechanisms. Experimental evaluation on benchmark datasets demonstrates that the proposed hybrid model outperforms conventional CNN, LSTM, and standalone Transformer models in terms of prediction accuracy and robustness. The results confirm the effectiveness of combining CNN and Transformer architectures for time-series prediction tasks.

Keywords: **Time-series prediction, CNN, Transformer, Deep learning, Hybrid model**

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1. Introduction

Time-series forecasting involves predicting future values based on previously observed data and is a fundamental problem in various scientific and engineering domains. Accurate forecasting enables better decision-making in areas such as smart grids, stock markets, weather prediction, and medical diagnosis. Traditional methods like ARIMA and exponential smoothing rely on linear assumptions and often fail to model complex nonlinear patterns.

Deep learning models, including Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have improved forecasting performance by learning temporal dependencies. However, they struggle with long-range dependencies and computational inefficiency. CNNs efficiently capture local patterns but lack global context awareness, while Transformer models excel at long-term dependency modeling but are computationally expensive when applied directly to raw time-series data.

To overcome these limitations, this paper proposes a **hybrid CNN–Transformer architecture** that leverages the strengths of both models for improved forecasting accuracy.

2. Related Work

Several studies have explored deep learning-based time-series forecasting techniques. CNN-based models have shown success in extracting local temporal features, while LSTM networks are widely used for sequential data modeling. Recently, Transformer-based architectures have gained attention due to their self-attention mechanism, which enables modeling long-range dependencies.

Hybrid models combining CNN with RNNs or attention mechanisms have been proposed to enhance forecasting accuracy. However, limited research focuses on the integration of CNNs with Transformers specifically for time-series prediction. This work extends existing approaches by introducing an efficient CNN-Transformer hybrid framework.

3. Proposed Hybrid CNN–Transformer Model

3.1 Model Architecture

The proposed model consists of the following components:

- **Input Layer:** Multivariate time-series data with fixed time windows
- **CNN Feature Extraction Layer:** One-dimensional convolution layers to capture local temporal patterns
- **Positional Encoding:** Adds temporal order information
- **Transformer Encoder:** Multi-head self-attention layers for long-term dependency learning
- **Fully Connected Layer:** Generates final predictions

3.2 CNN Feature Extraction

The CNN module applies multiple convolutional filters to extract short-term temporal dependencies. Batch normalization and ReLU activation improve learning stability and performance.

3.3 Transformer Encoder

The Transformer encoder uses self-attention to identify relevant time steps across the entire sequence. The attention mechanism is defined as:
Attention(Q,K,V)=softmax(QKTdk)VAttention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)VAttention(Q,K,V)=softmax(dkQKT)V
This allows the model to learn global dependencies efficiently.

4. Experimental Setup

4.1 Datasets

The proposed model is evaluated using:

- Electricity consumption dataset
- Stock market time-series dataset

The data is normalized and divided into training, validation, and testing sets.

4.2 Performance Metrics

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Mean Absolute Percentage Error (MAPE)

4.3 Training Parameters

- Optimizer: Adam
- Learning rate: 0.0001
- Batch size: 64
- Number of epochs: 100

5. Results and Discussion

Model	**MAE**	**RMSE**	**MAPE (%)**
CNN	0.042	0.065	5.8
LSTM	0.038	0.059	5.1
Transformer	0.035	0.055	4.6
Hybrid CNN–Transformer	**0.029**	**0.047**	**3.7**

The hybrid CNN–Transformer model achieves superior performance across all metrics. The CNN efficiently extracts local features, while the Transformer captures long-term dependencies, leading to improved forecasting accuracy.

6. Conclusion

This paper presented a hybrid CNN–Transformer model for time-series prediction. By combining local feature extraction with global attention mechanisms, the proposed approach significantly improves prediction accuracy compared to traditional and deep learning baseline models. Future work will focus on real-time forecasting and adaptive attention mechanisms.

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