NEURAL INFORMATION PROCESSING SYSTEMS

MIX: A Multi-view Time-Frequency Interactive Explanation Framework for Time Series Classification

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NeurIPS 2025

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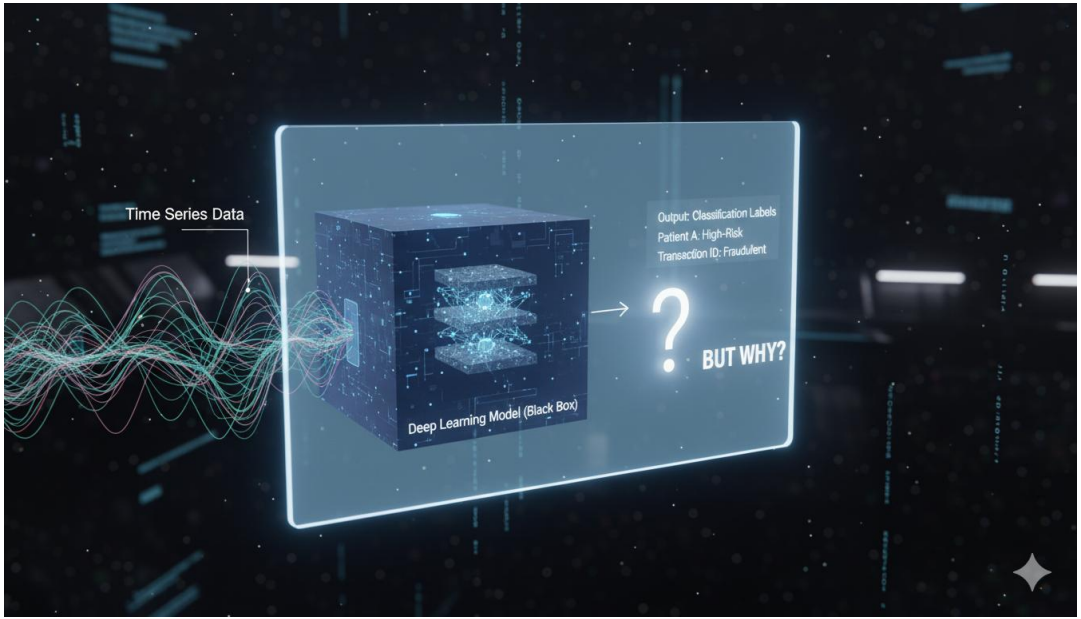
Funded by the European Union

The Challenge: Black Box Time Series Models

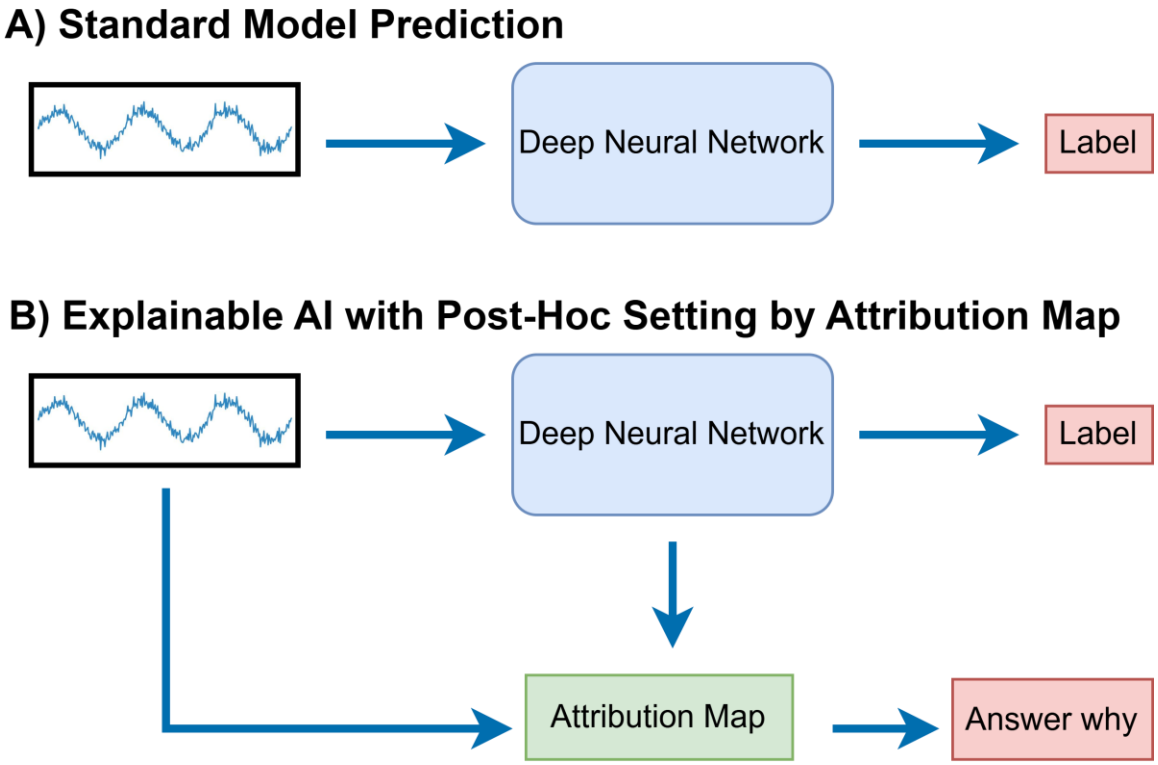
Time Series Classification (TSC) is critical in fields like healthcare and finance. While Deep Learning (DL) models offer state-of-the-art performance, they are often "black boxes."

The Problem:

- Lack of Transparency: Why did the model make a specific prediction?
- Trust and Accountability: Crucial in sensitive applications.
- Debugging: Understanding model failures is difficult without interpretability.



Current Post-Hoc Explanation Methods

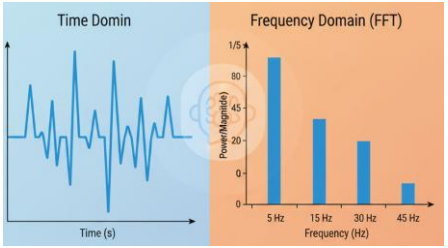


Limitations of Current Explanation Methods

Current approaches often provide an incomplete picture.

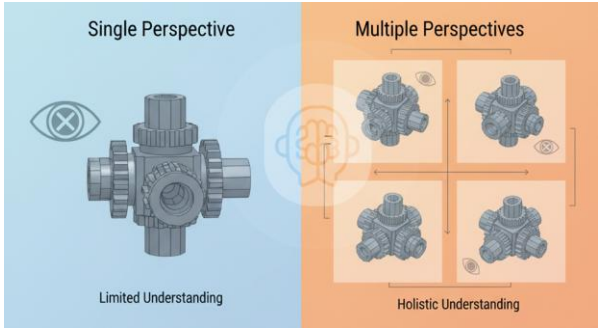
1. Single-Domain Focus

- Most methods operate only in the time domain.
- This ignores valuable information present in the frequency domain (e.g., cycles, seasonality).



2. Single-View Perspective

- They analyze the time series from a single, fixed perspective.
- This can lead to explanations that are not robust or faithful to the model's true reasoning.

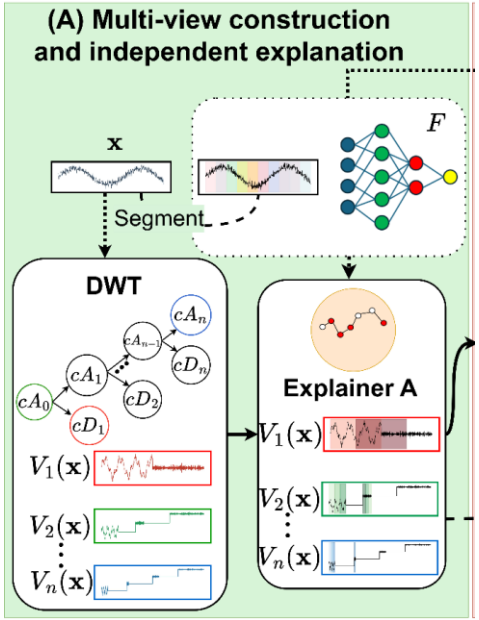


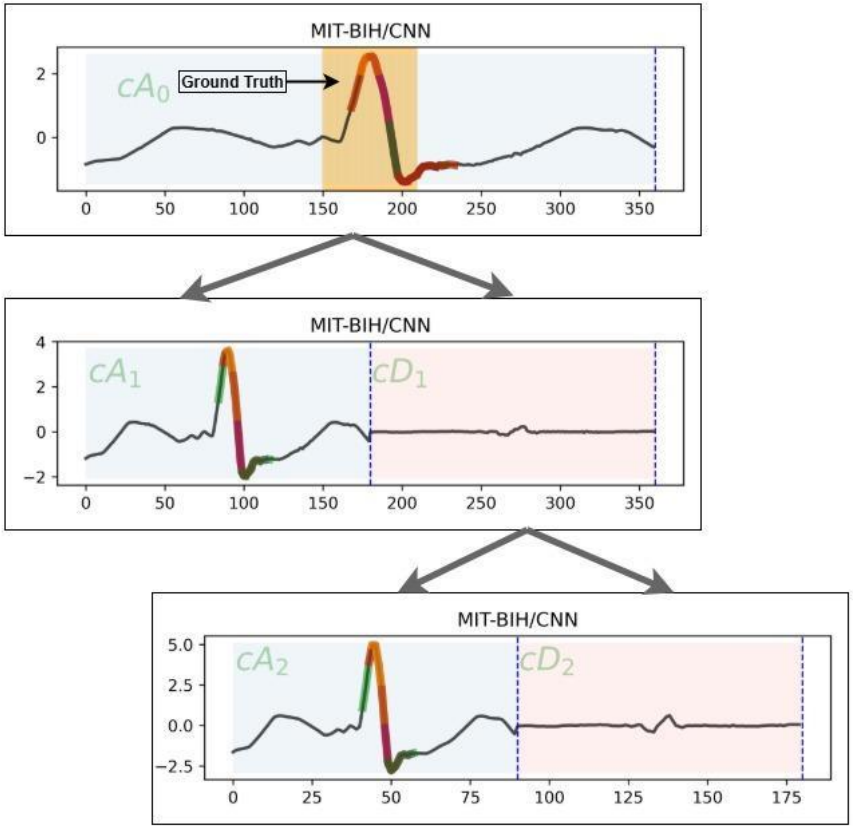
Our Solution: The MIX Framework

We introduce MIX (Multi-view Interactive eXplanation Framework), a novel approach that addresses limitations.

Multi-view Analysis

Generate **multiple time-frequency "views"** using the Haar Discrete Wavelet Transform (DWT).





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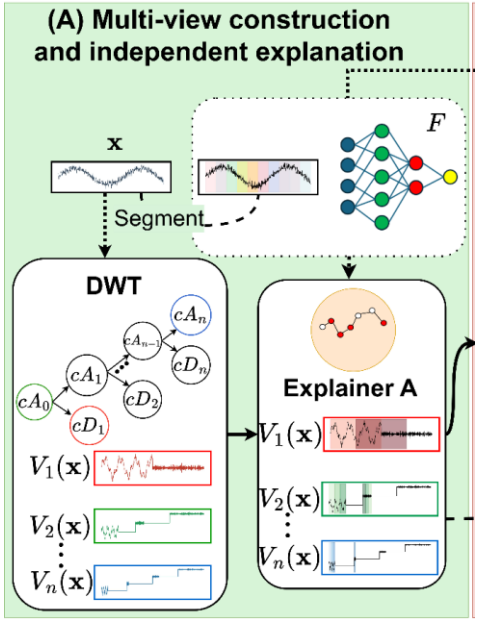
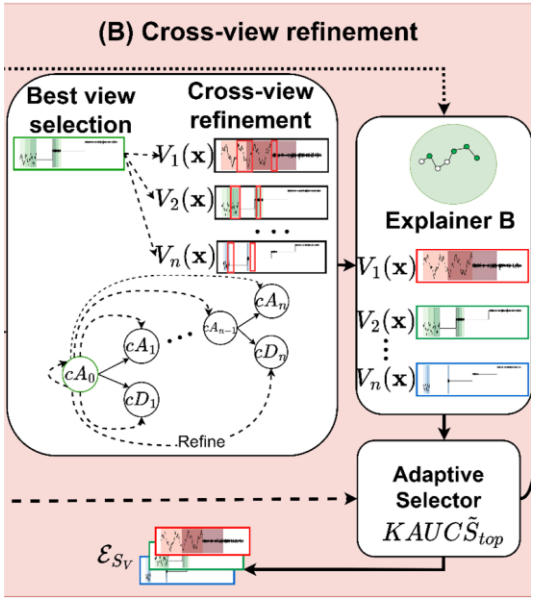
Interactive Refinement

Leverage information from **one view** to refine and improve the explanations in other views.





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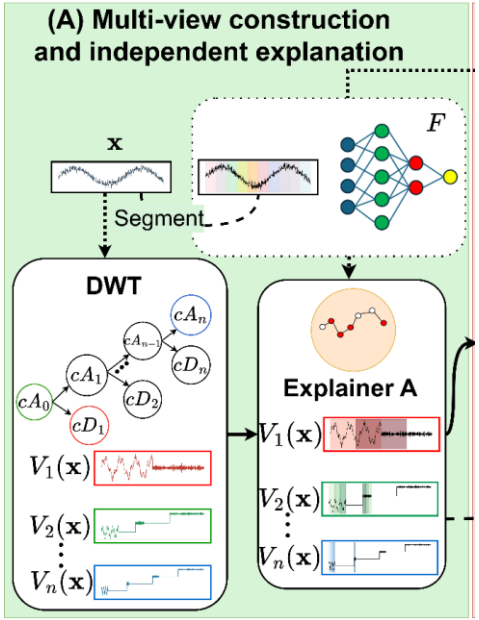
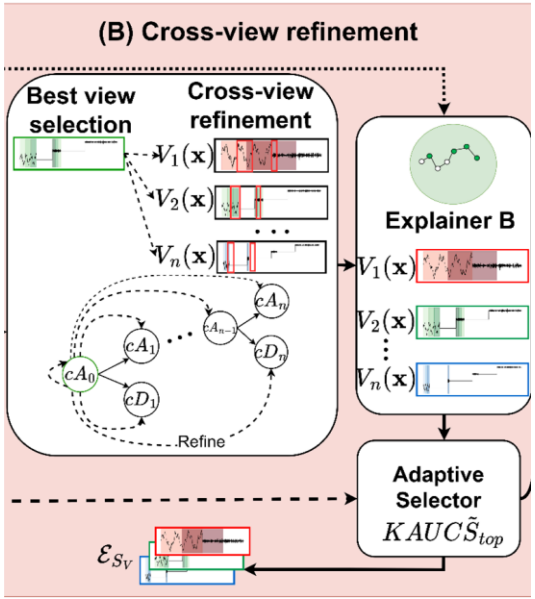
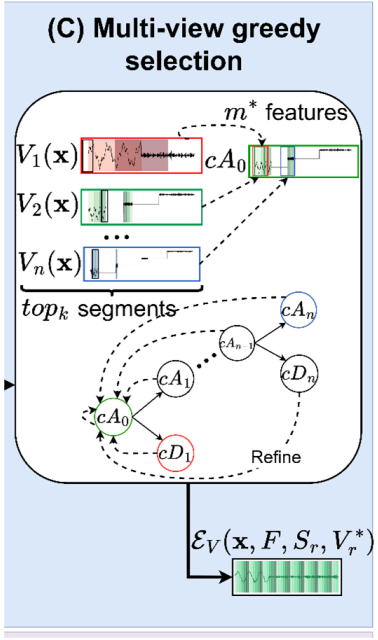
User-Centric Explanations

Map the most important features back to the time domain for intuitive understanding.







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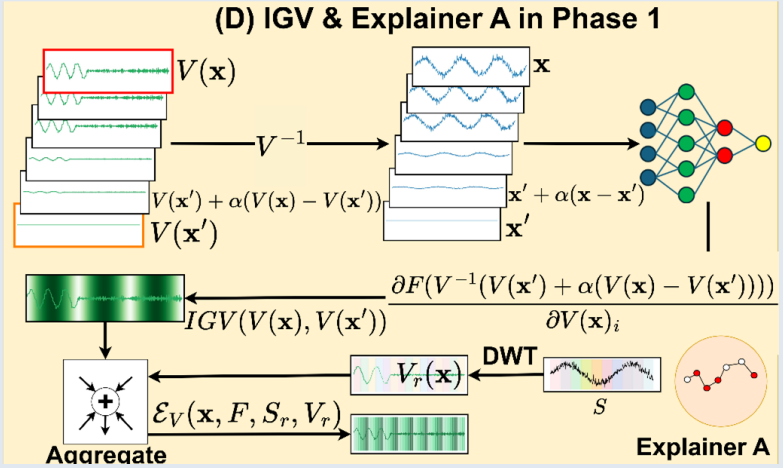
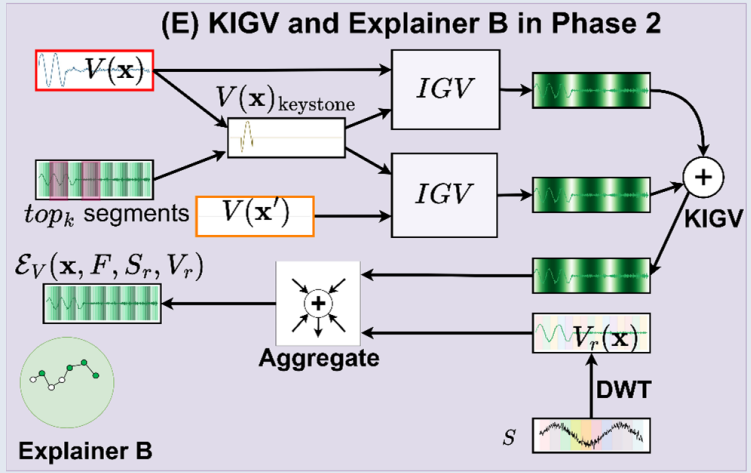
Phase 1: IGV & Explainer A



Phase 2: KIGV & Explainer B



The MIX Framework

(A) Multi-view Construction

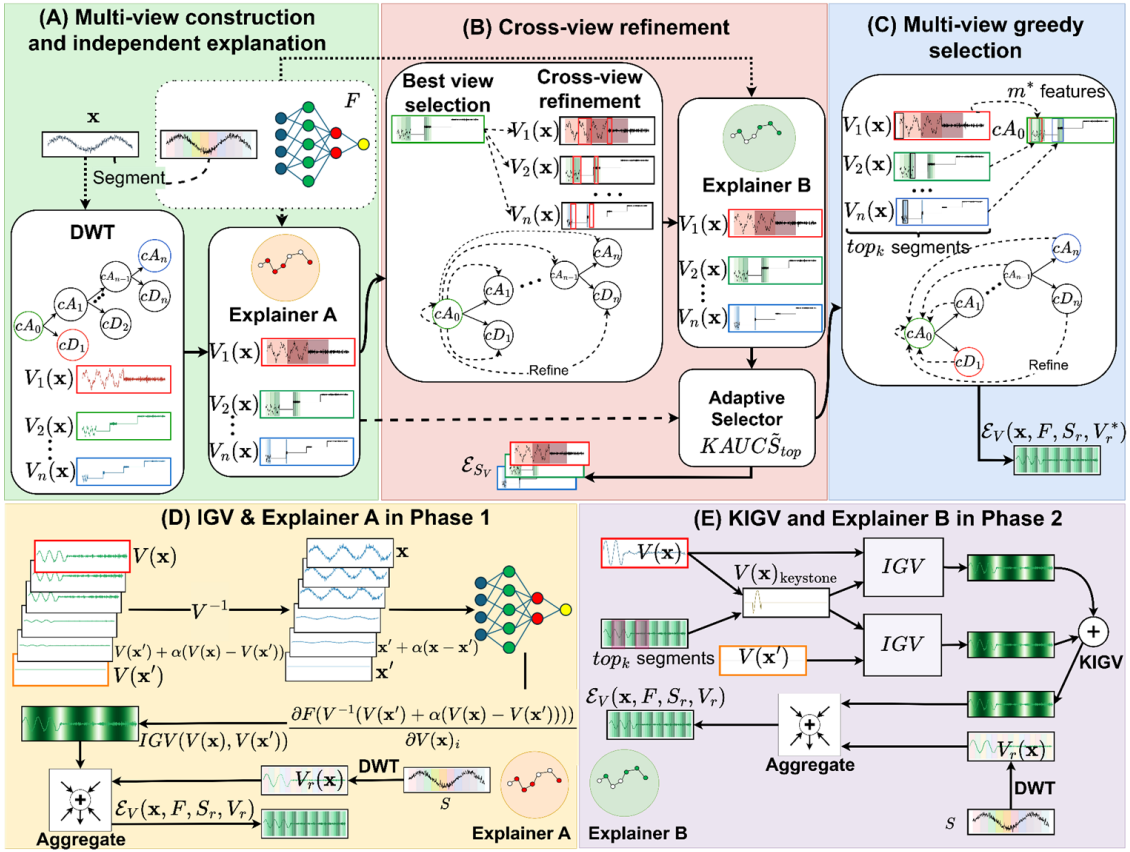
Generate views via DWT & create initial explanations.

(B) Cross-view Refinement

"Best" view's explanation refines others.

(C) Greedy Selection

Aggregate most important features from all views.



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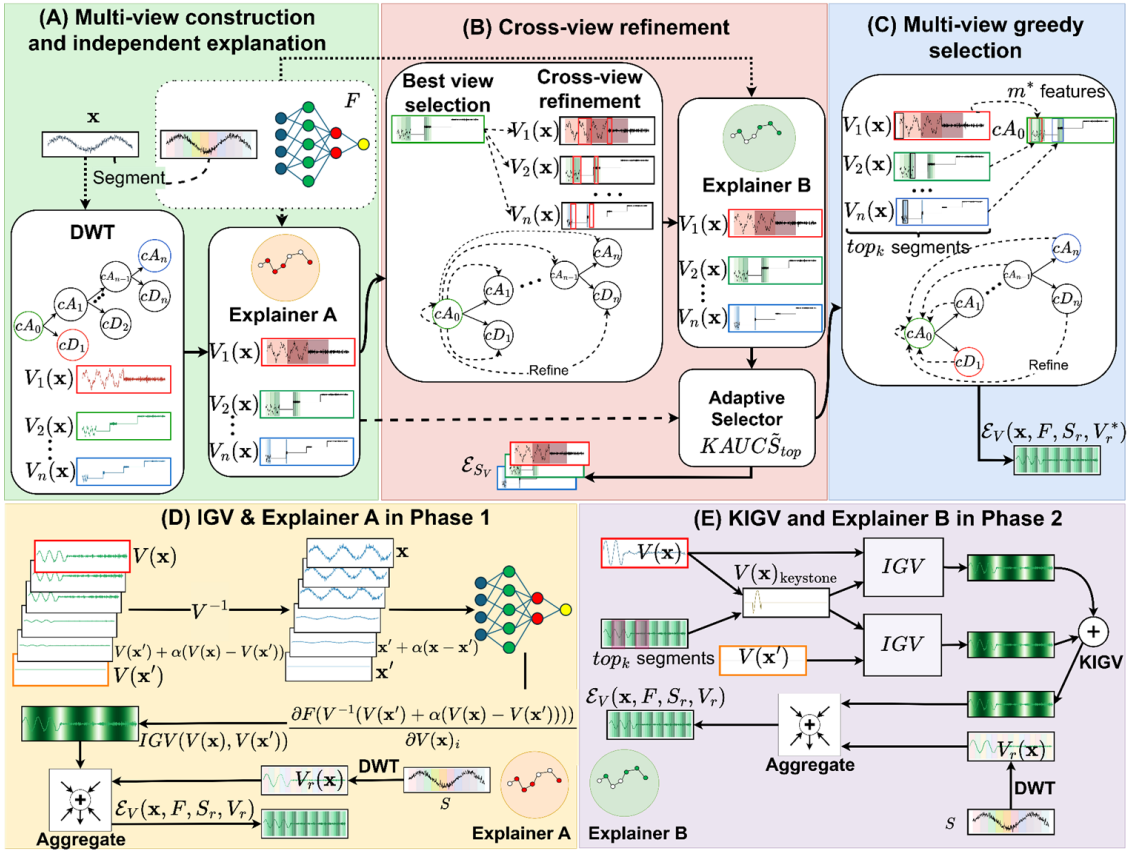


Experimental Setup

Data

Datasets

11 UCR datasets (time series)

Synthetic dataset (known ground truth)

MIT-BIH ECG dataset (expert annotations)

Models

Models

ResNet-34

BiLSTM

Transformer

Compare

Baselines

LIMESegment

InteDisUX

SpectralX

Metrics

Metrics

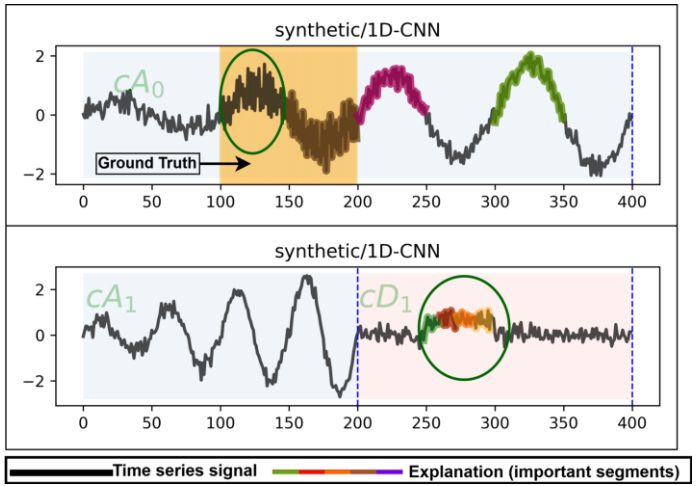
Faithfulness & Robustness

Ground Truth Alignment (AUPRC, Jaccard)

Qualitative Visualizations

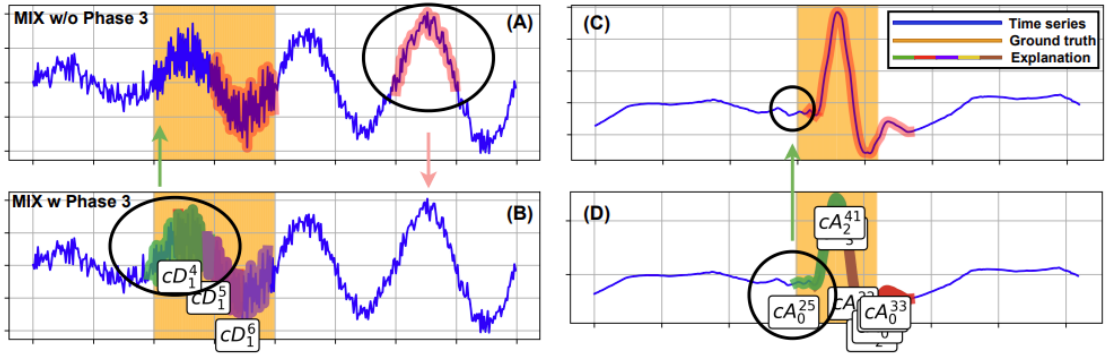
Synthetic Dataset

On synthetic data with a known ground truth, MIX with Phase 3 correctly identifies the important features in the detail coefficients (cD^1), which are obscured by noise in the raw view (cA^0).



MIT-BIH (ECG Data)

On real-world ECG data, Phase 3 aggregates key segments from multiple wavelet levels (e.g., cA^2, cA^3) to form a more complete and accurate explanation than relying on a single view.



Key Results: MIX Outperforms SOTA

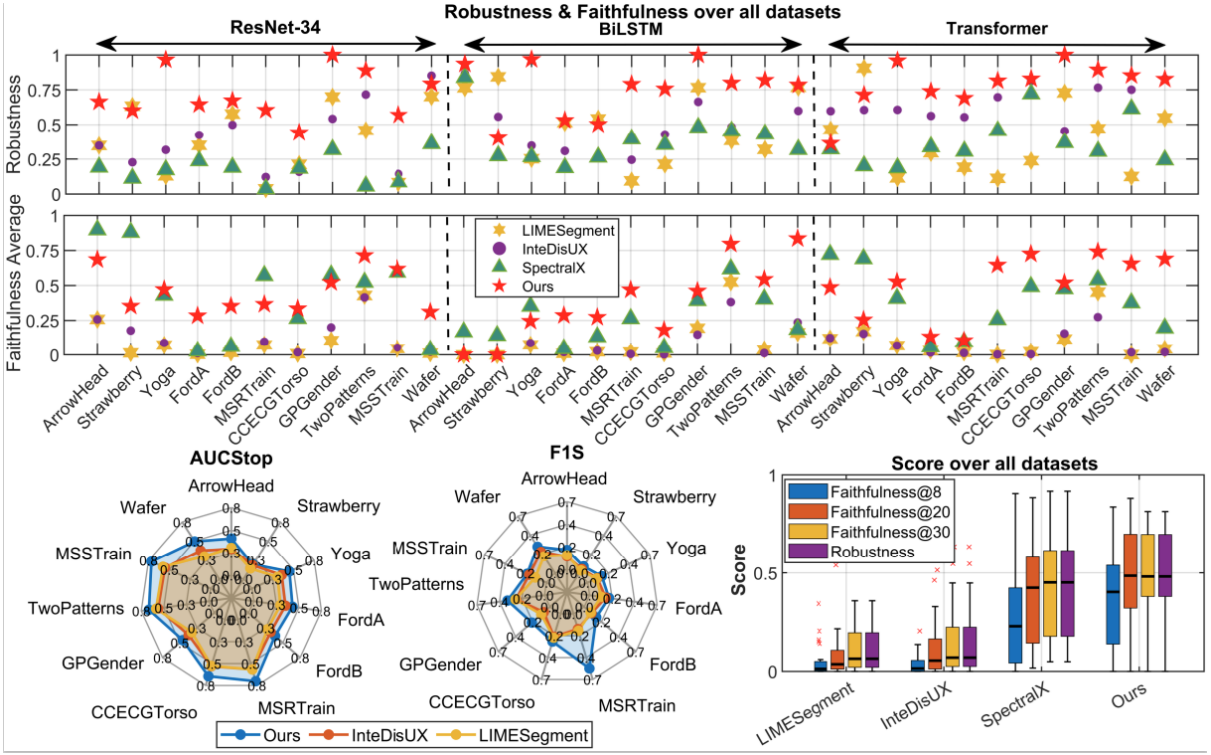
Across 33 configurations, MIX demonstrates superior performance.

24/33

Faithfulness Wins

27/33

Robustness Wins



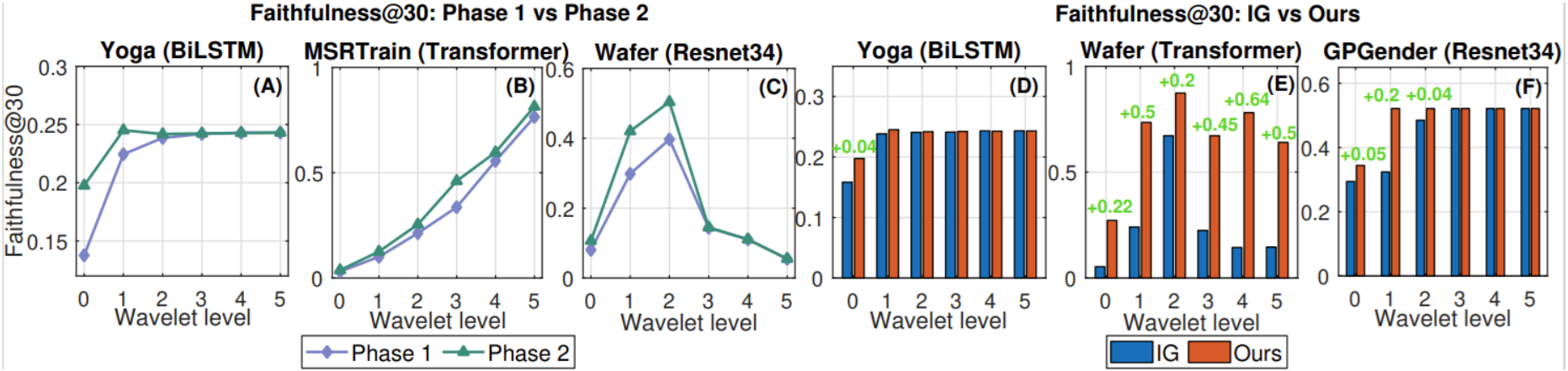
Ablation Studies: Why MIX Works

Cross-View Refinement

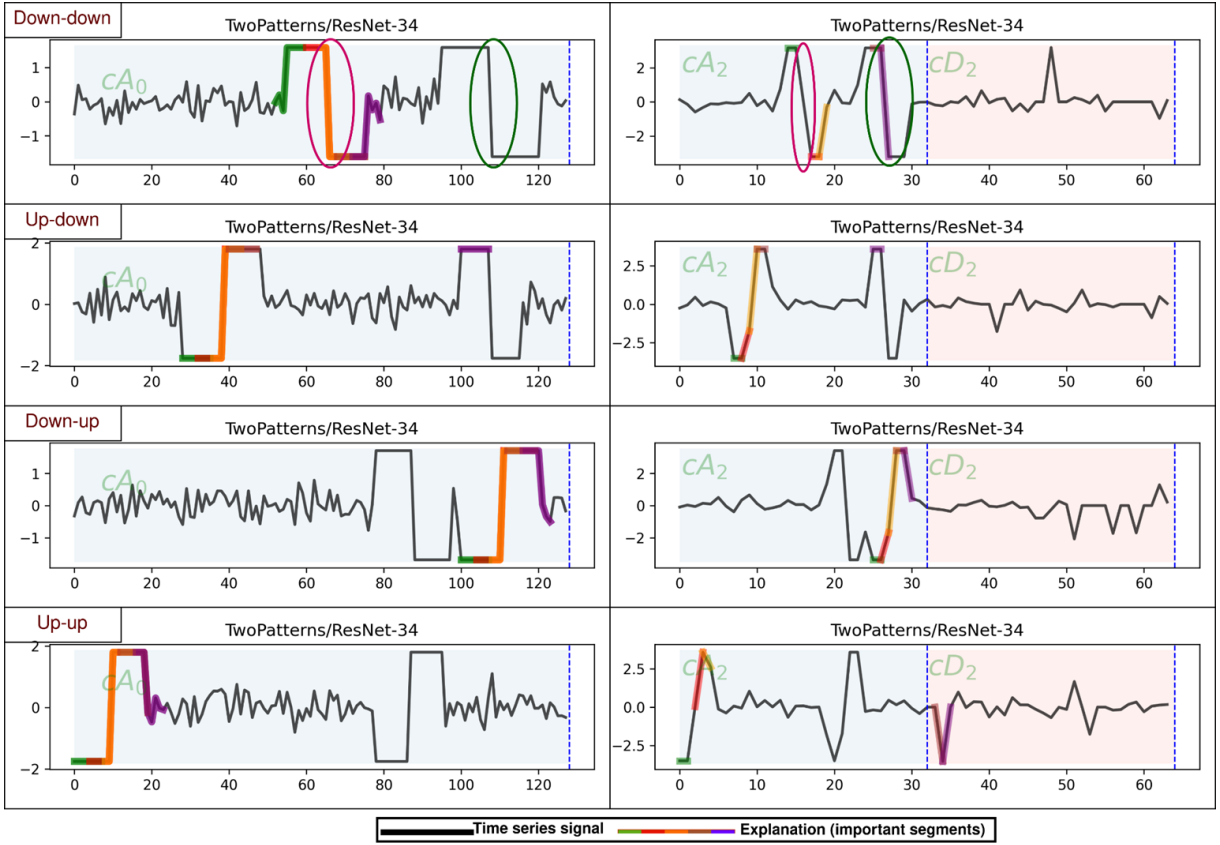
Consistently improved explanation faithfulness across all tests.

Attribution Mechanism

OSIGV/KIGV demonstrated higher faithfulness than standard IG.



Qualitative Visualizations



Analysis:

- Observation: The raw view (cA^0) can miss key patterns or highlight noise (see "down-down" class example).
- Insight: A different view at a higher wavelet level (cA^2) provides a cleaner, more accurate explanation.
- Conclusion: No single view is always best. MIX's ability to leverage multiple views is crucial for robust explanations.

Conclusion & Future Directions

A summary of our achievements and a roadmap for what's next.

Contributions

- ★ **A novel multi-view framework (MIX) for TSC explanation.**
- ★ **An interactive cross-view refinement scheme.**
- ★ **New, robust attribution mechanisms (OSIGV & KIGV).**
- ★ **A greedy selection strategy for user-centric explanations.**

Future Work

- ➢ Explore explanation for multivariate time series.
- ➢ Develop a global explanation framework for time series classification.

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Thank you!

Questions?

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