AI FOR EARLY DETECTION OF FETAL ABNORMALITIES

----- GROUP - 16 -----
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INTRODUCTION

The Clinical Need for AI in Fetal Abnormality Detection

- Fetal abnormalities such as brain malformations and arrhythmias often go undetected during early pregnancy.
- Traditional methods (ultrasound, ECG) depend on clinician expertise and vary in accuracy.
- Existing AI tools are typically single-modality and lack generalizability.
- **Our Goal:** Build a multi-modal AI system combining ultrasound and ECG data for accurate, real-time, non-invasive fetal abnormality detection.

PROBLEM STATEMENT

Clinical Challenge

Fetal abnormalities like CSP, LV malformations, and arrhythmias often go undetected until late.

Early diagnosis is critical to prevent neonatal morbidity and developmental delays.

Limitations of Current Methods

Ultrasound interpretation is subjective and operator-dependent.

Existing AI tools are mostly single-modality and miss multi-system issues.

Technical Gap

Lack of models that combine spatial features (ultrasound) with temporal patterns (ECG).

Few models provide clinically explainable outputs (e.g., Grad-CAM, waveform anomalies).

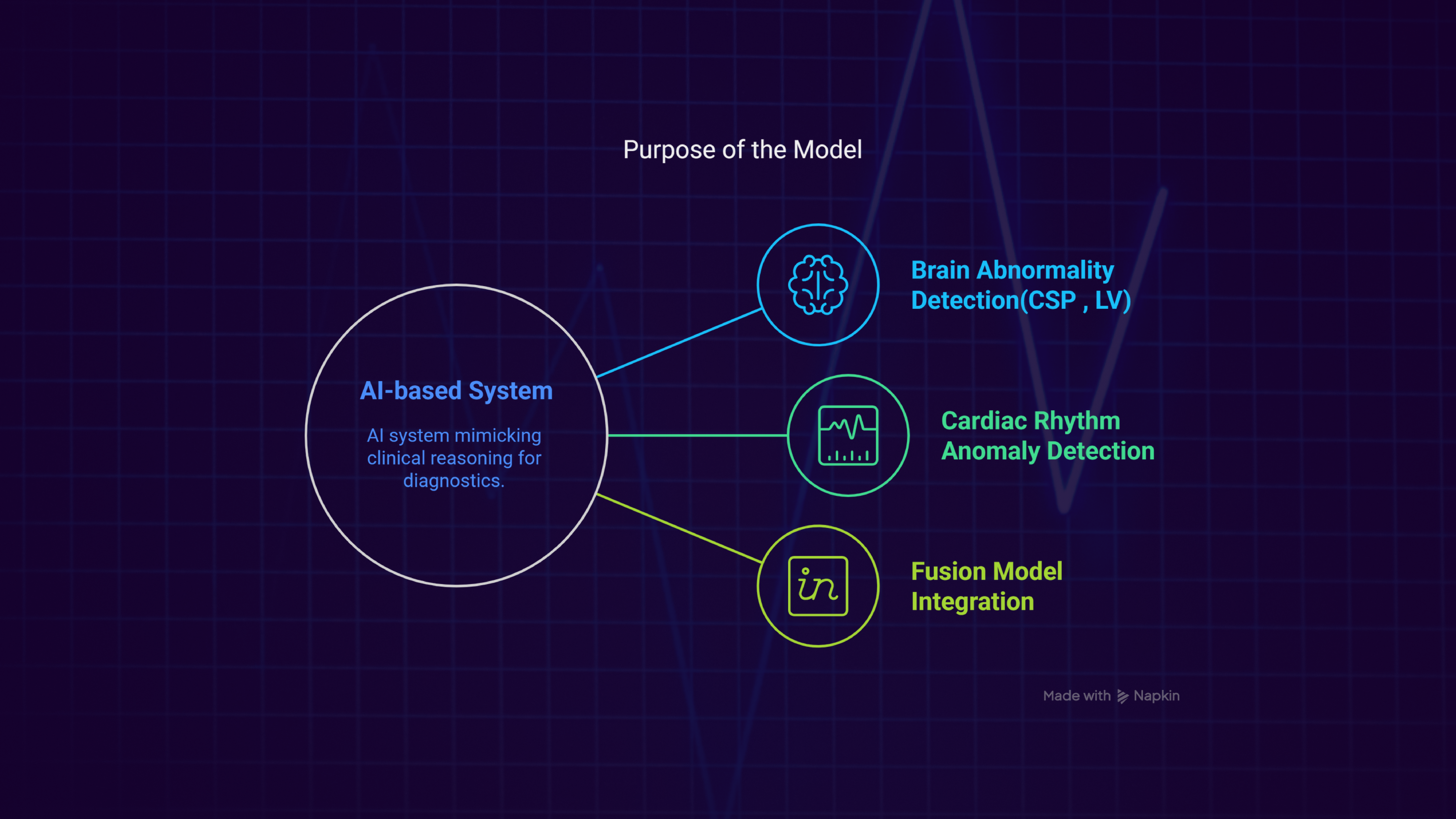
Our Motivation

Build a multi-modal AI system that mirrors clinical decision-making.

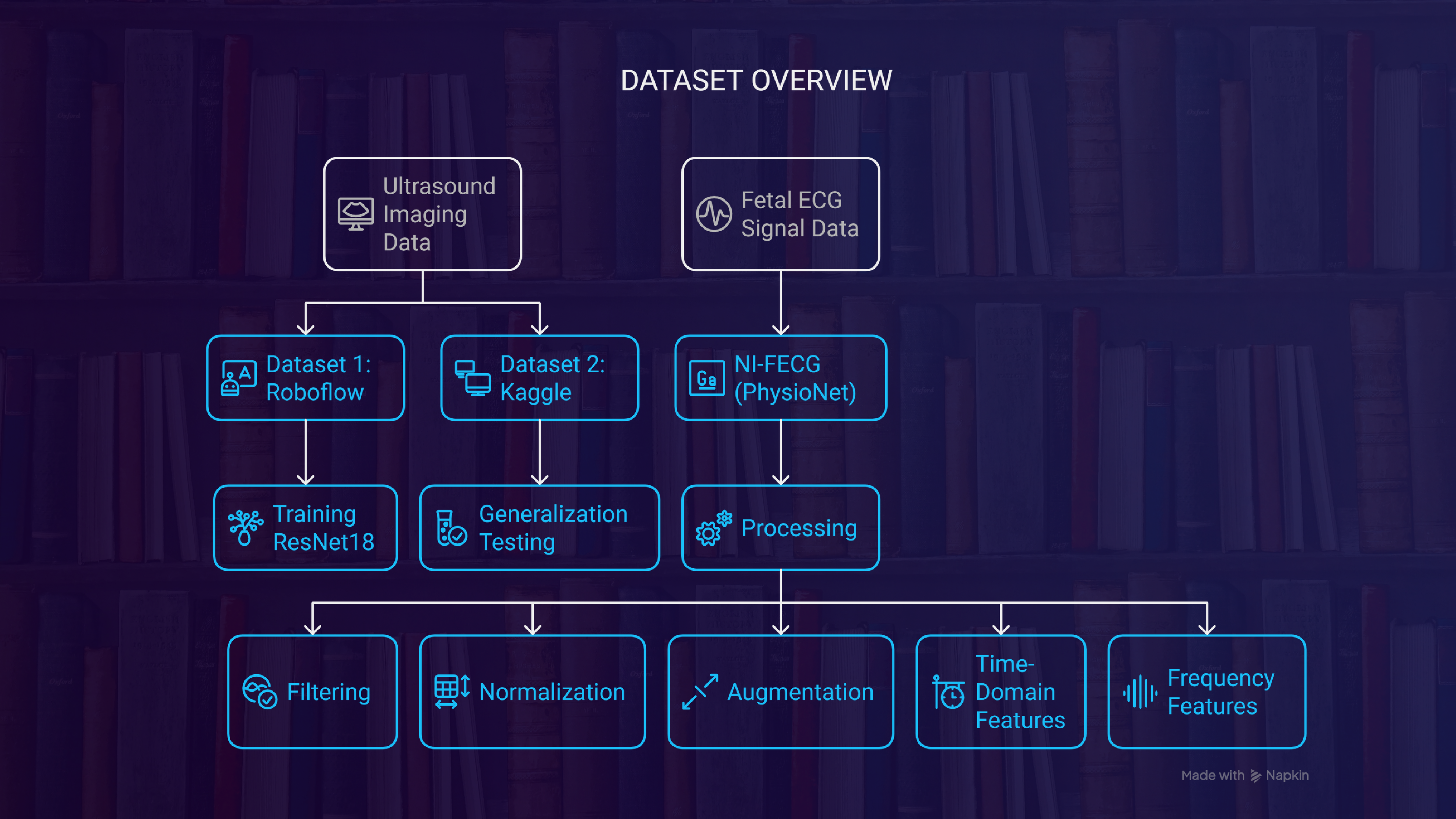
Integrate ultrasound + ECG to deliver a unified, non-invasive, real-time abnormality prediction.

LITERATURE REVIEW

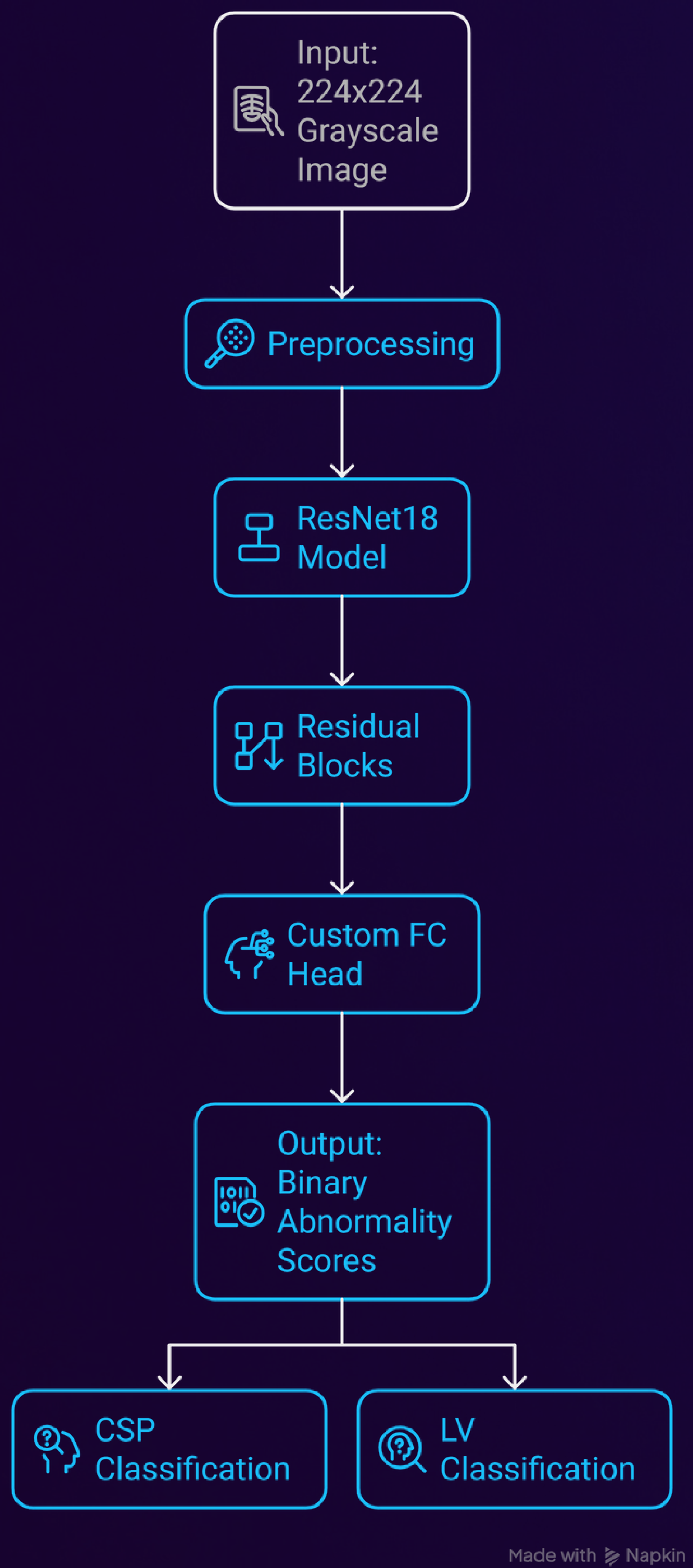
Source	Focus	Model/Approach	Key Result	Relevance to Our Work
Sonio Suspect (FDA, 2024) [1]	Ultrasound-based anomaly detection	AI-assisted fetal imaging system	↑ 22% anomaly detection	Validates AI's role in clinical ultrasound analysis
Zeng et al., 2021 (JDI) [2]	Fetal head segmentation	Attention-Gated V-Net	Accuracy: 86.4%	Baseline for imaging; our ResNet18 directly targets CSP & LV
LightGBM (ArXiv, 2023) [9]	ECG-based fetal classification	Feature-based ML model	Accuracy: 98.31%	Highlights ECG's diagnostic value; our Bi-LSTM adds temporal context
Our Model (Fusion AI)	Multi-modal abnormality detection	ResNet18 + CNN-BiLSTM + Fusion NN	F1 = 0.9722, Accuracy = 96.46%, Recall = 100%	Outperforms prior work with robust multi-modal, explainable AI

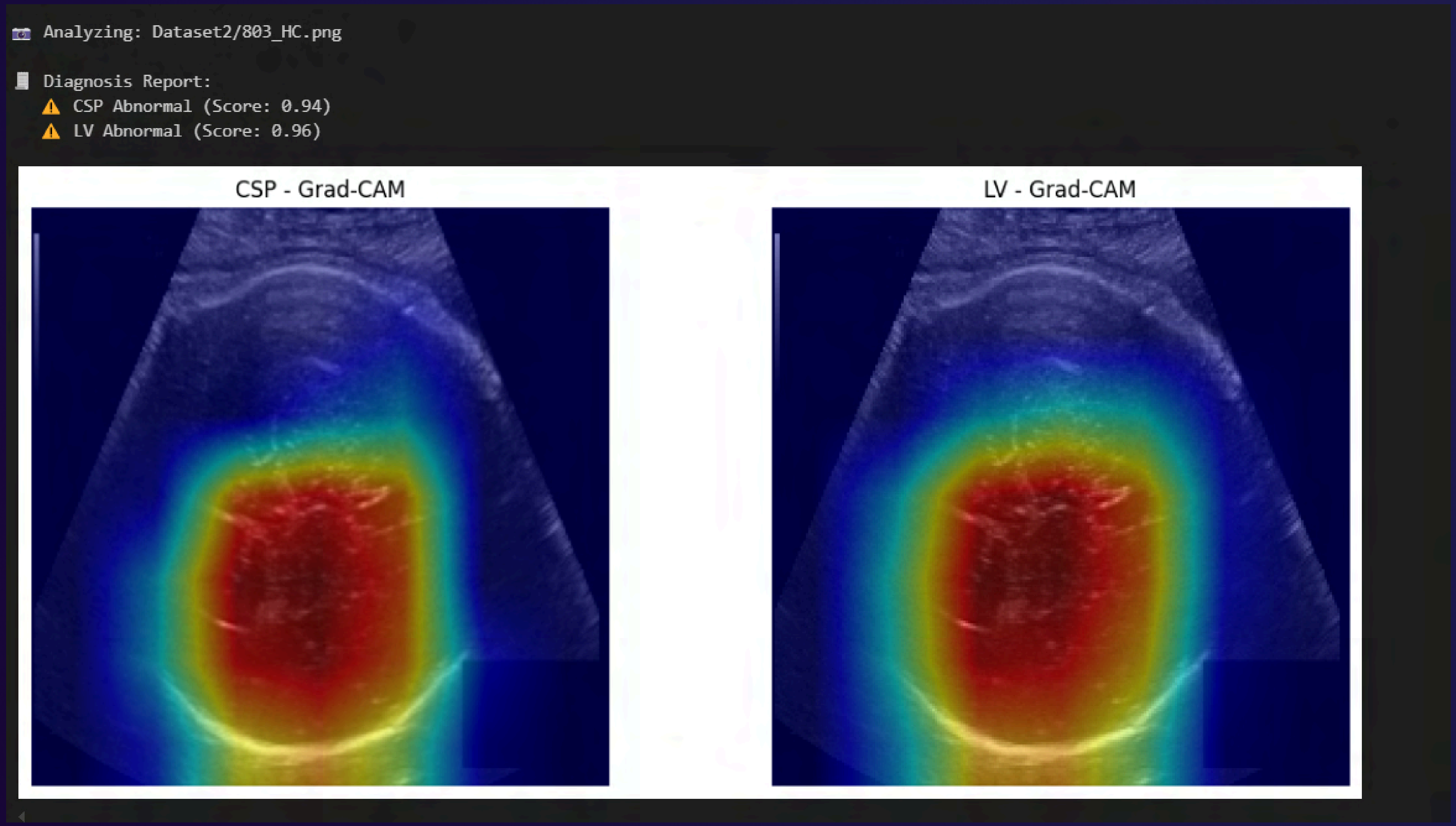


Purpose of the Model
AI-based System
AI system mimicking clinical reasoning for diagnostics.
Brain Abnormality Detection(CSP , LV)
Cardiac Rhythm Anomaly Detection
Fusion Model Integration
Made with Napkin


DATASET OVERVIEW
Ultrasound Imaging Data
Fetal ECG Signal Data
Dataset 1: Roboflow
Dataset 2: Kaggle
NI-FECG (PhysioNet)
Training ResNet18
Generalization Testing
Processing
Filtering
Normalization
Augmentation
Time-Domain Features
Frequency Features
Made with Napkin

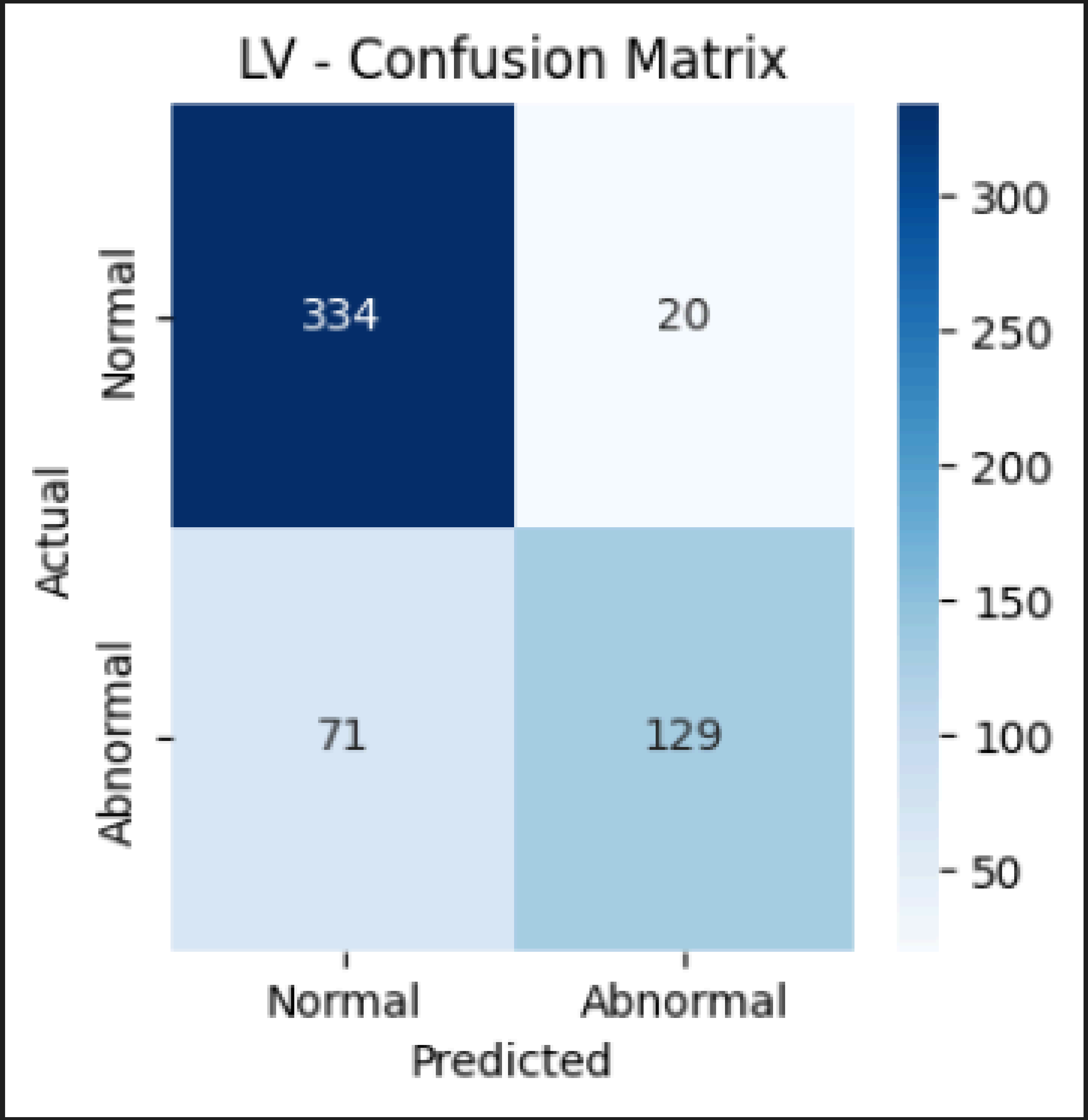
ULTRASOUND - ARCHITECTURE & RESULT





🧠 LV:

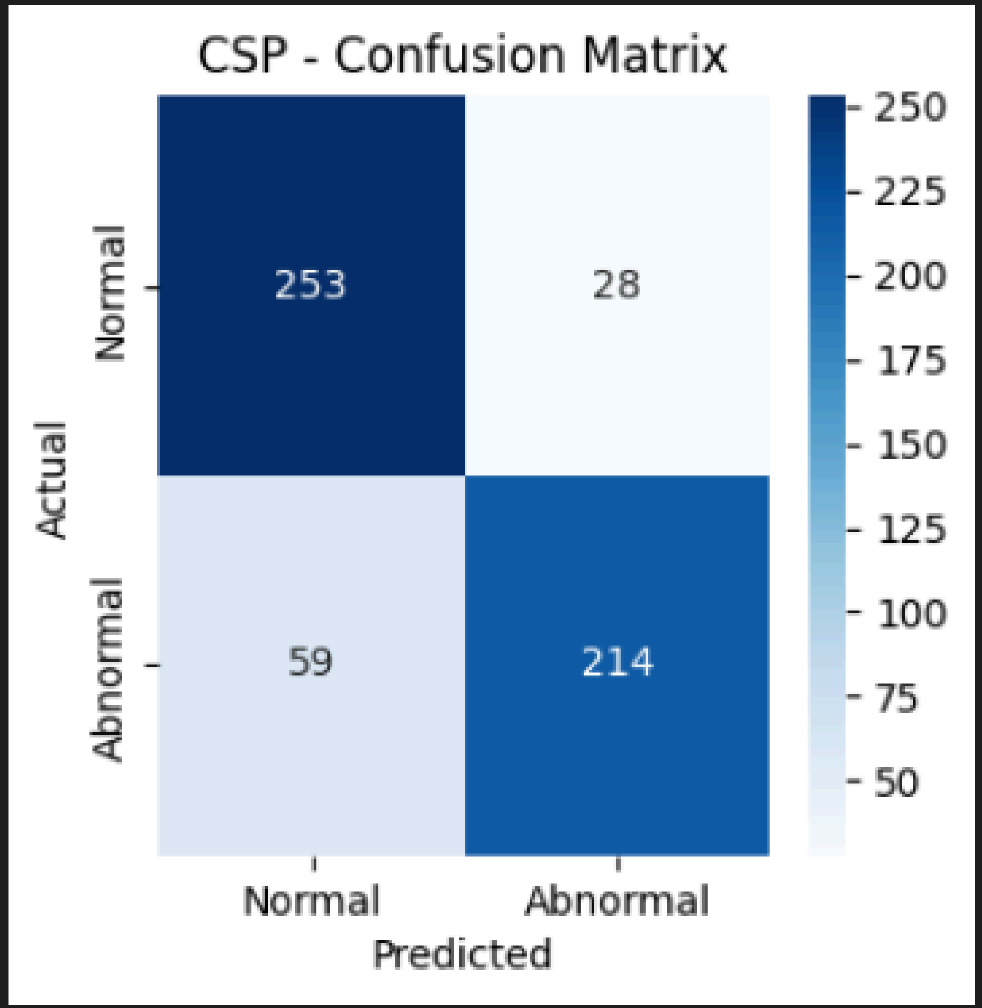
Accuracy: 0.8357 | Precision: 0.8658 | Recall: 0.6450 | F1: 0.7393 | AUROC: 0.8964



📊 Evaluation Metrics:

🧠 CSP:

Accuracy: 0.8430 | Precision: 0.8843 | Recall: 0.7839 | F1: 0.8311 | AUROC: 0.9207



ECG - ARCHITECTURE & RESULT

🔐 Confidence Stats:
🟩 Normal: 0.984 ± 0.049
🟥 Abnormal: 0.941 ± 0.075

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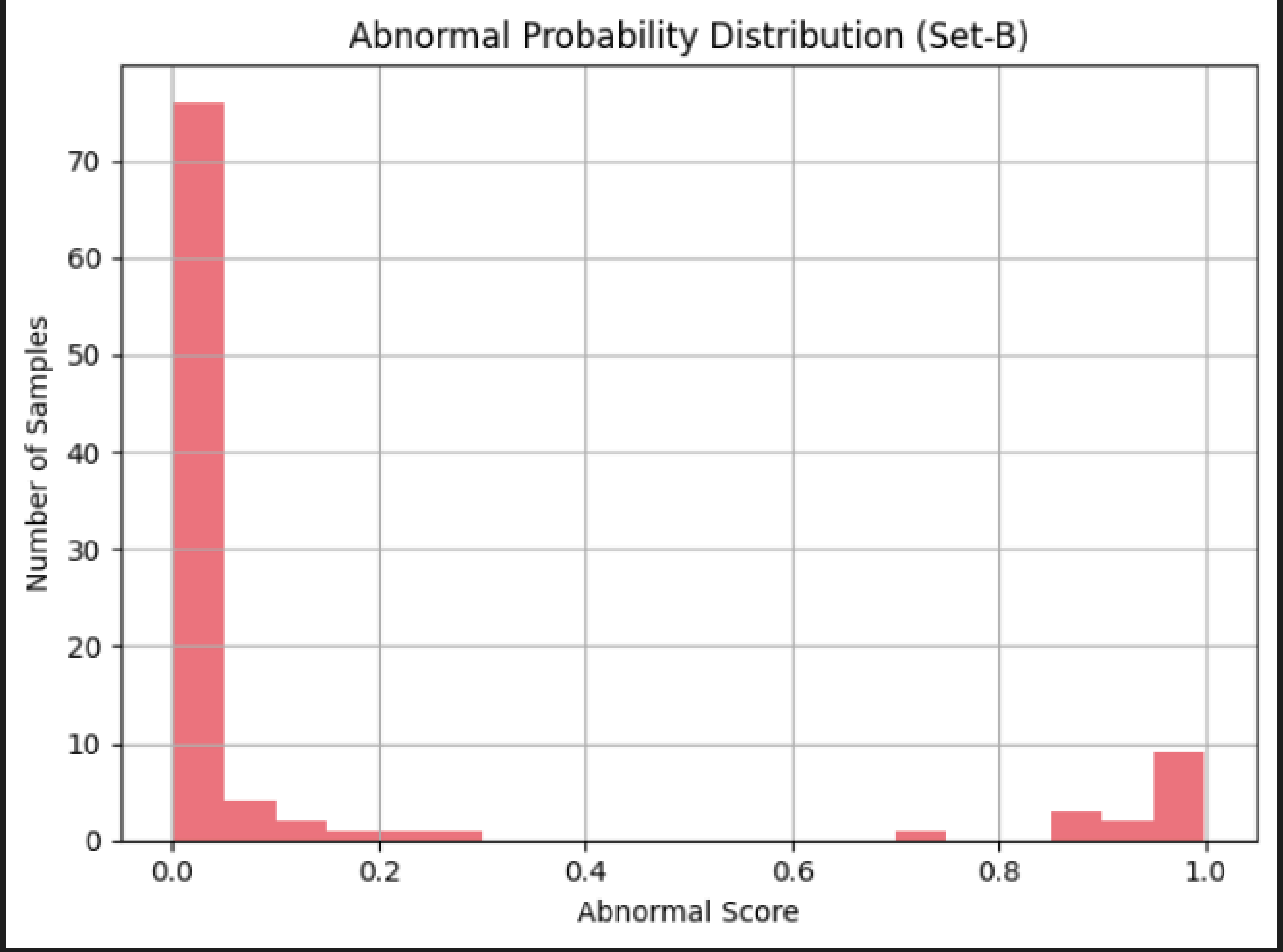


Input Data — Receives a 10-second, 4-channel fetal ECG segment

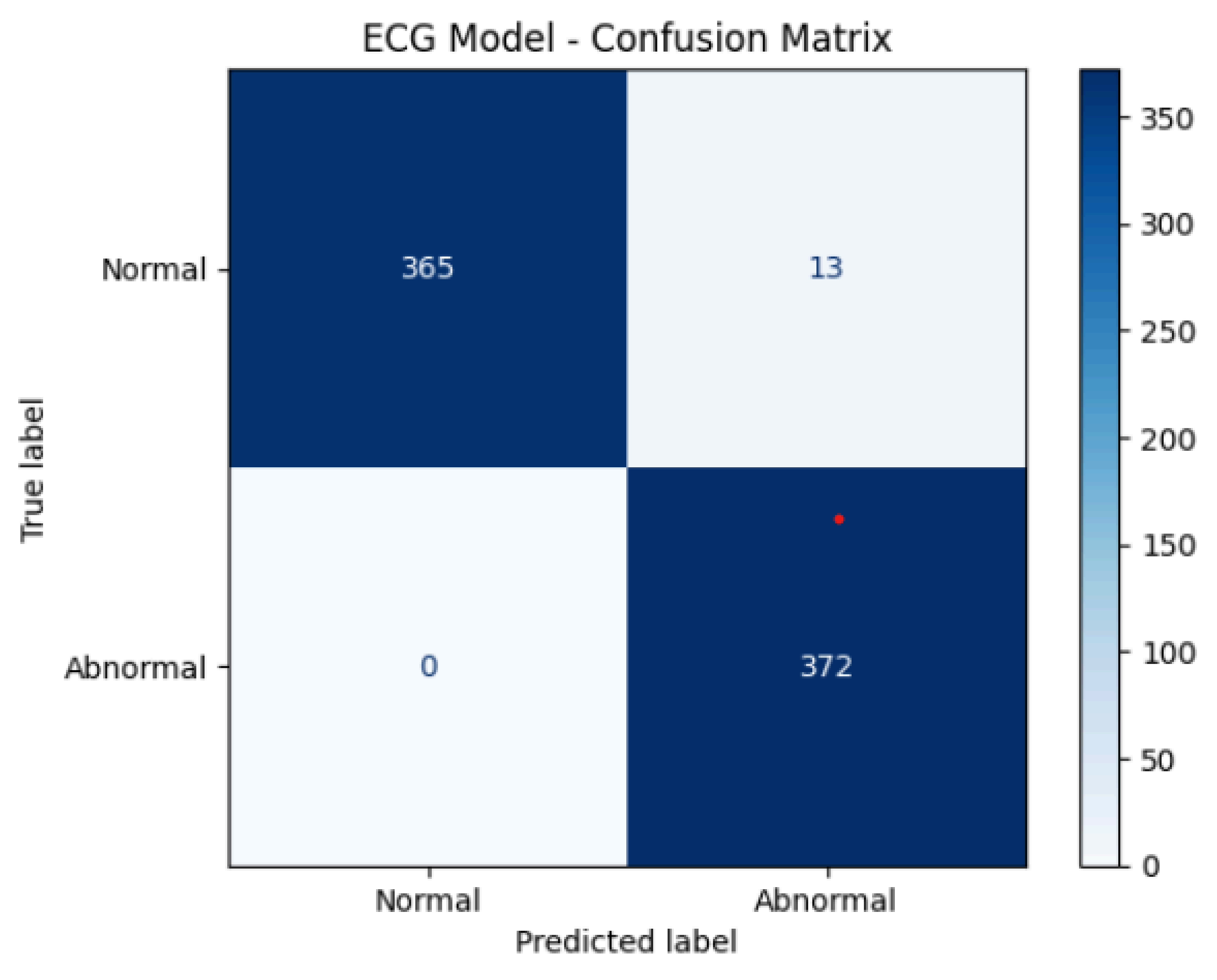
1D CNN — Extracts waveform morphology like QRS, P, and T waves

Bi-LSTM — Captures bidirectional rhythm patterns and sequences

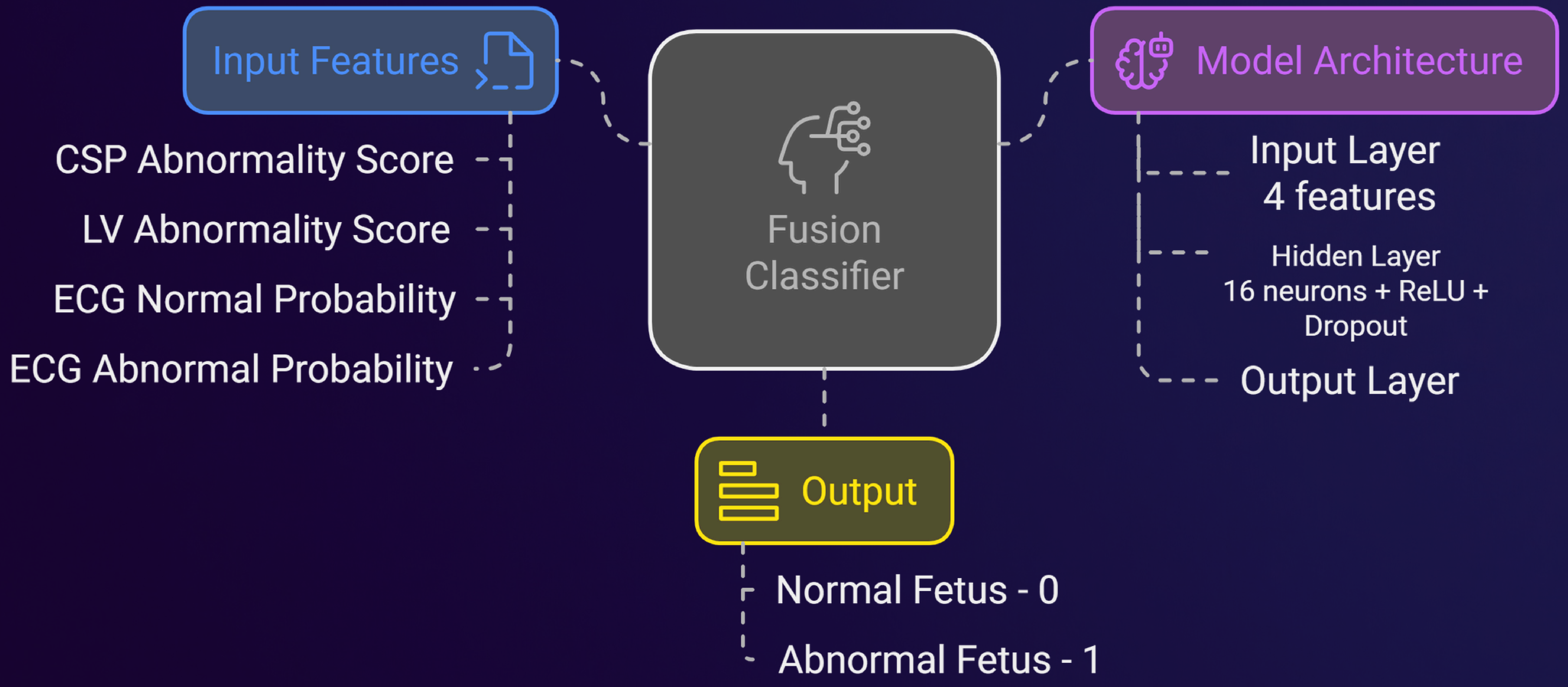
Fully Connected Layers — Performs classification based on extracted features

Output Classification — Provides a binary classification of normal (0) or abnormal (1)

📊 Evaluation Metrics:
✅ Accuracy : 0.9827
✅ Precision : 0.9831
✅ Recall : 0.9828
✅ F1 Score : 0.9827



FUSION CLASSIFIER

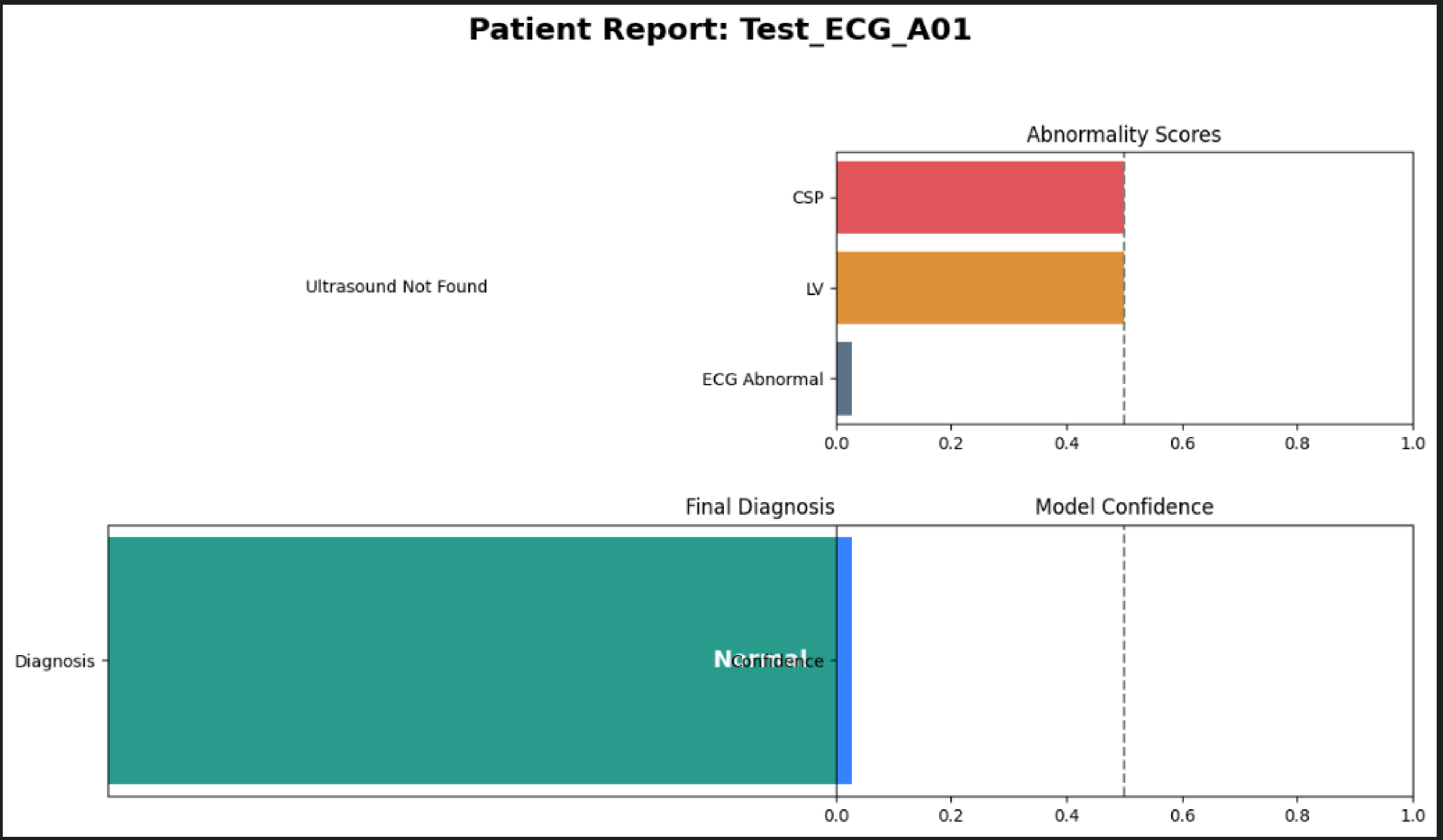


```
Diagnosing Patient: Test_ECG_A01
Mode: ECG-only
❤ ECG Abnormal Score: 0.028

Final Diagnosis: 🟩 Normal
:\Users\kasar\AppData\Local\Temp\ipykernel_1636\2859743732.py:40: FutureWarning:

assing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=scores, y=labels, palette=colors)
✅ Report saved to: ./reports\Test_ECG_A01_report.png
```




```
Mode: Fusion (ECG + US)
CSP: 0.033 | LV: 0.008
❤ ECG Abnormal Score: 0.028

Final Diagnosis: 🟩 Normal
C:\Users\kasar\AppData\Local\Temp\ipykernel_1636\2859743732.py:40: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect

  sns.barplot(x=scores, y=labels, palette=colors)
✅ Report saved to: ./reports\Test_Fusion_report.png
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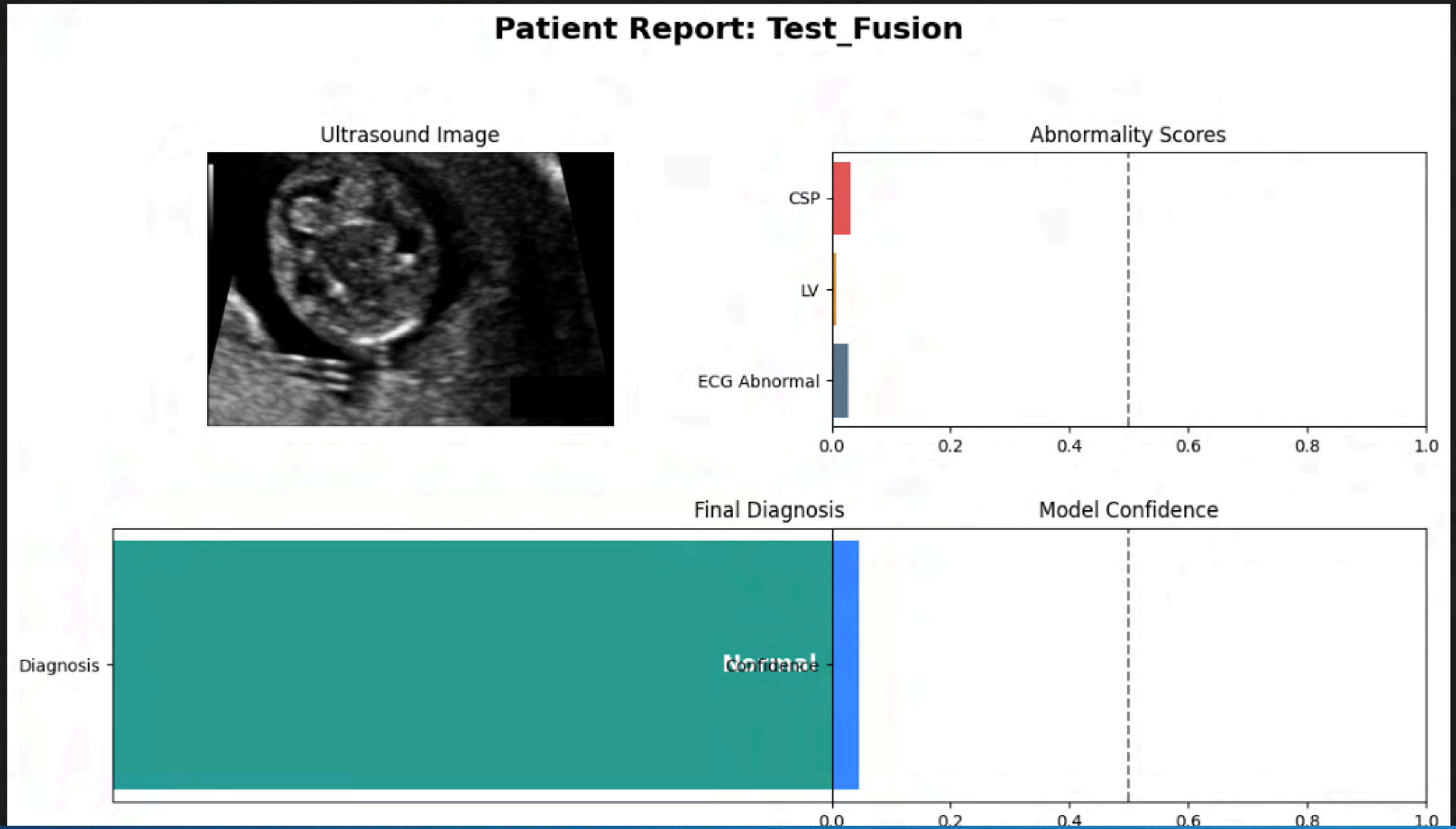

CONCLUSION

- Developed a multi-modal AI model for fetal abnormality detection.
- Combines ultrasound imaging with ECG signal processing for comprehensive diagnosis.
- Outperforms existing benchmarks in F1, recall, and accuracy.
- Fully interpretable with Grad-CAM and signal-based insights.
- Real-time compatible, non-invasive, and clinically deployable.

FUTURE WORK

- Expand dataset diversity, deploy web interface, real-time uploads.
- Real-Time Web-Based Interface
- Test model robustness across datasets from different hospitals and regions.

CITATIONS

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THANK YOU