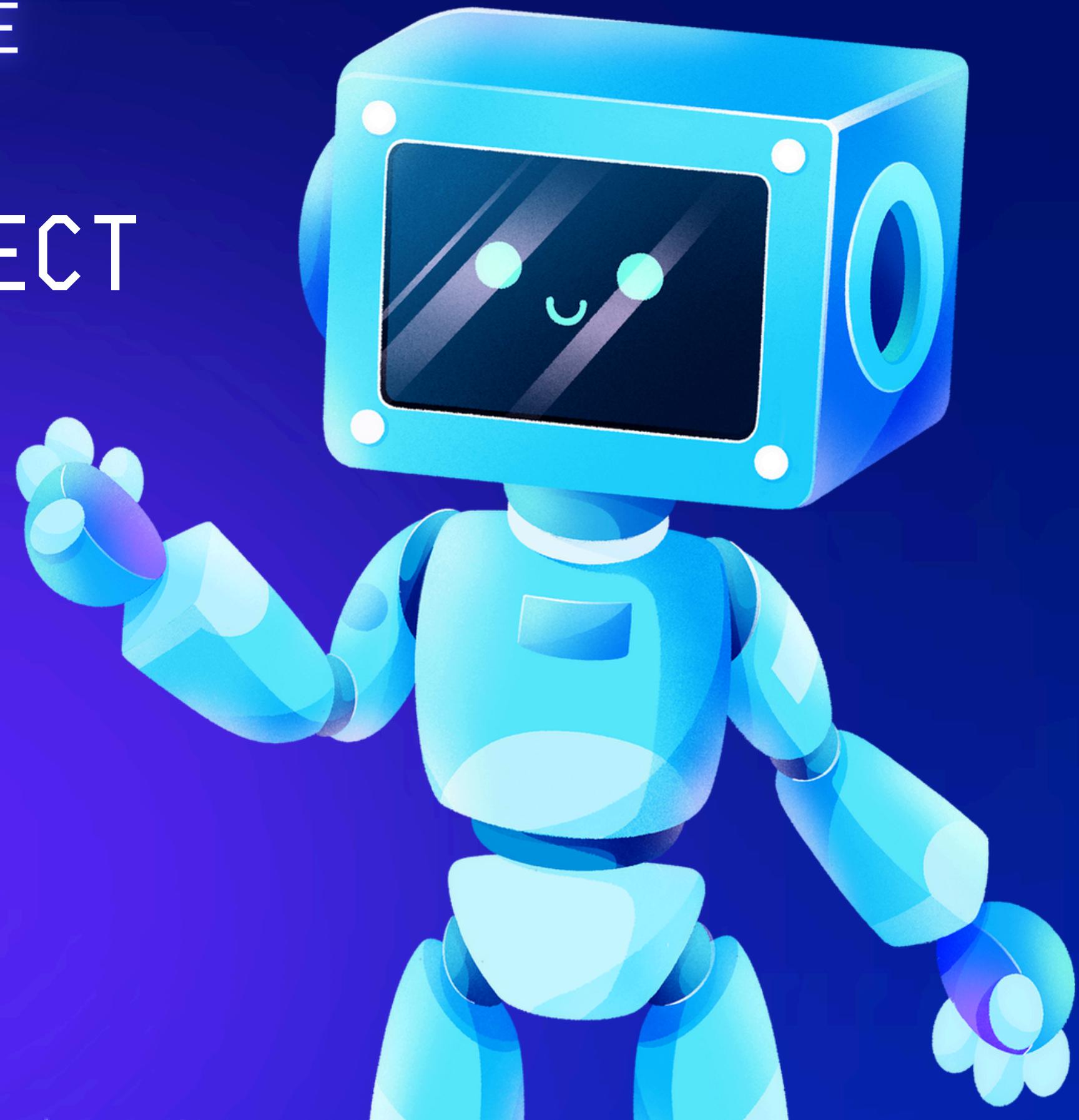


ARTIFICIAL INTELLIGENCE

# NEURAL NETWORKS PROJECT

AREEEBA TAHIR

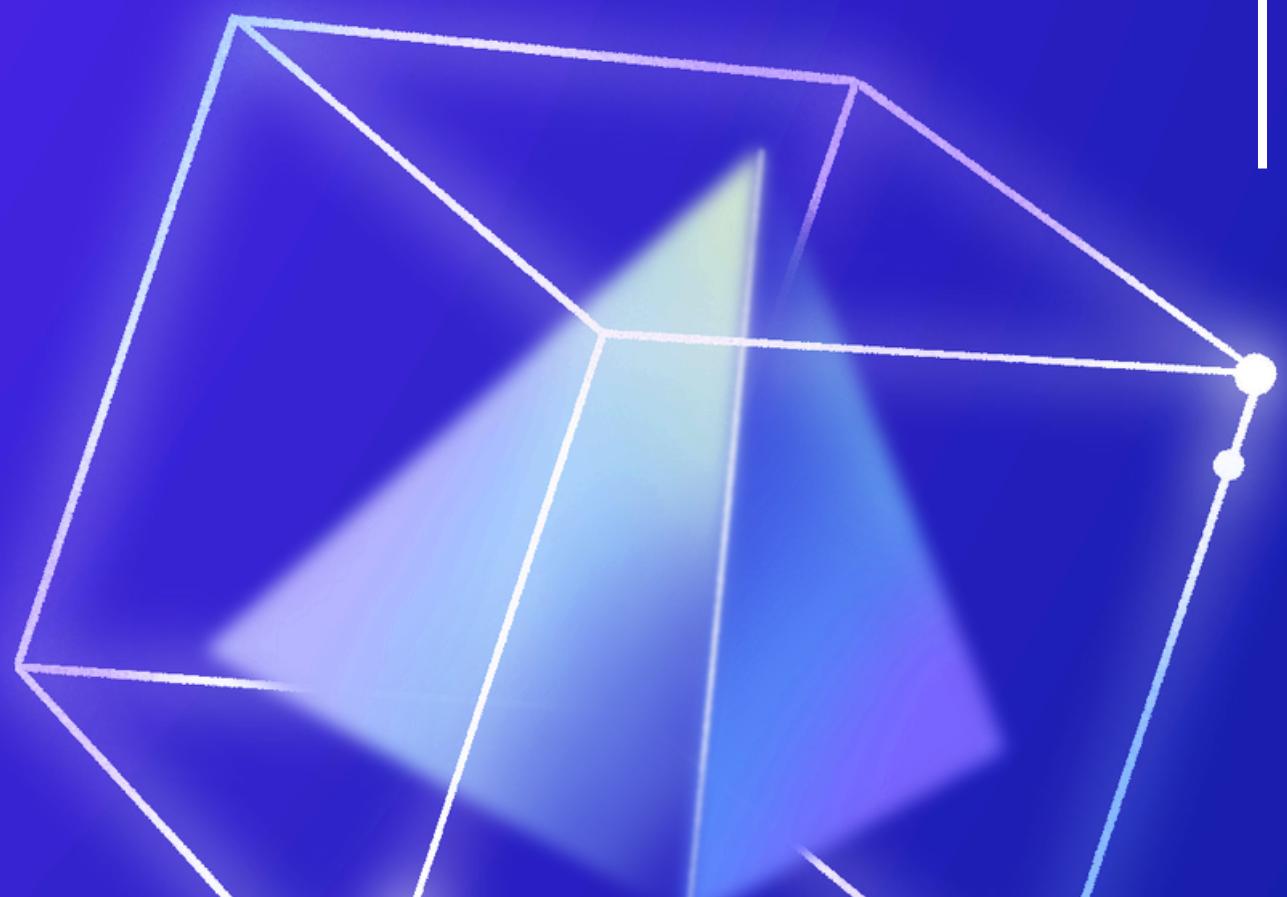
SP23-BAI010





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# MIT-BIH Arrhythmia Dataset

## Dataset Dimensions

### AttributeValueDescription

Samples (Rows)

~109,000 to 130,000

Each row represents one heartbeat segment  
(centered around an R-peak).

### Features (Cols)

- 140-180 columns (typically 140)  
Each column is an ECG amplitude value (time-series points per heartbeat).
- Label Column (Column 140 or 'label')
  - Type: Integer (0 to 4).
  - Class Mapping:
    - 0: Normal beat (N)
    - 1: Supraventricular premature beat (S)
    - 2: Premature ventricular contraction (V)
    - 3: Fusion beat (F)
    - 4: Unclassifiable beat (Q)



# Real-World Problems Solved by LSTM Models on the MIT-BIH Arrhythmia Dataset

## • 1. Early Detection of Life-Threatening Arrhythmias

Problem: Missed diagnosis of irregular heartbeats (e.g., Ventricular Tachycardia) can lead to sudden cardiac death.

LSTM Solution:

- Analyzes ECG signals in real-time to flag high-risk arrhythmias (e.g., PVCs, AFib).
- Impact: Reduces reliance on manual review by cardiologists, speeding up emergency interventions.

Example:

- Hospitals use LSTM-powered monitors in ICUs to alert staff about critical arrhythmias.

## 2. Remote Patient Monitoring (RPM)

Problem: Chronic heart patients need continuous monitoring outside hospitals.

LSTM Solution:

- Integrates with wearable ECG devices (e.g., Apple Watch, Holter monitors).
- Detects anomalies in real-time and sends alerts to doctors.
- Impact: Prevents hospital readmissions by catching issues early.

Example:

- Companies like AliveCor use similar AI models for at-home ECG analysis.

# MODEL ARCHITECTURE

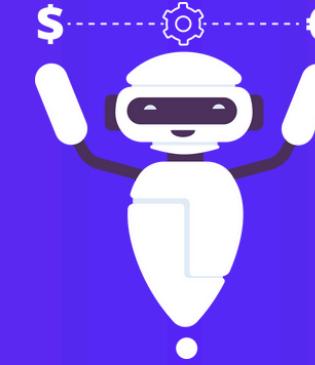


## LSTM Model Architecture

**Input:** ECG signals shaped as (187 timesteps, 1 feature)

- 1.
- 2.
- 3.
- 4.
5.
  - LSTM (64 units) → Returns sequences (return\_sequences=True)
  - Dropout (30%) → Reduces overfitting
  - LSTM (64 units) → Outputs last timestep.
  - Dense (128, ReLU) → Adds non-linearity.
  - Dropout (10%) → Further regularization.
  - Dense (5, Softmax) → Classifies into 5 arrhythmia types.

# Advantages of Using LSTM



Advantages of LSTM for ECG Arrhythmia Detection:

- \* Time-Series Mastery - Perfect for ECG's sequential nature
- \* Memory Power - Remembers long-term heartbeat patterns
- \* Adaptable Length - Handles variable-duration heartbeats
  - \* High Accuracy - 96-97% on MIT-BIH dataset
  - \* Noise Resistant - Tolerates signal imperfections
- \* Explainable - Attention shows decision-making segments

# PROJECT SCOPE



## COMPARITIVE TABLE

Model

Dataset

key Hyperparams

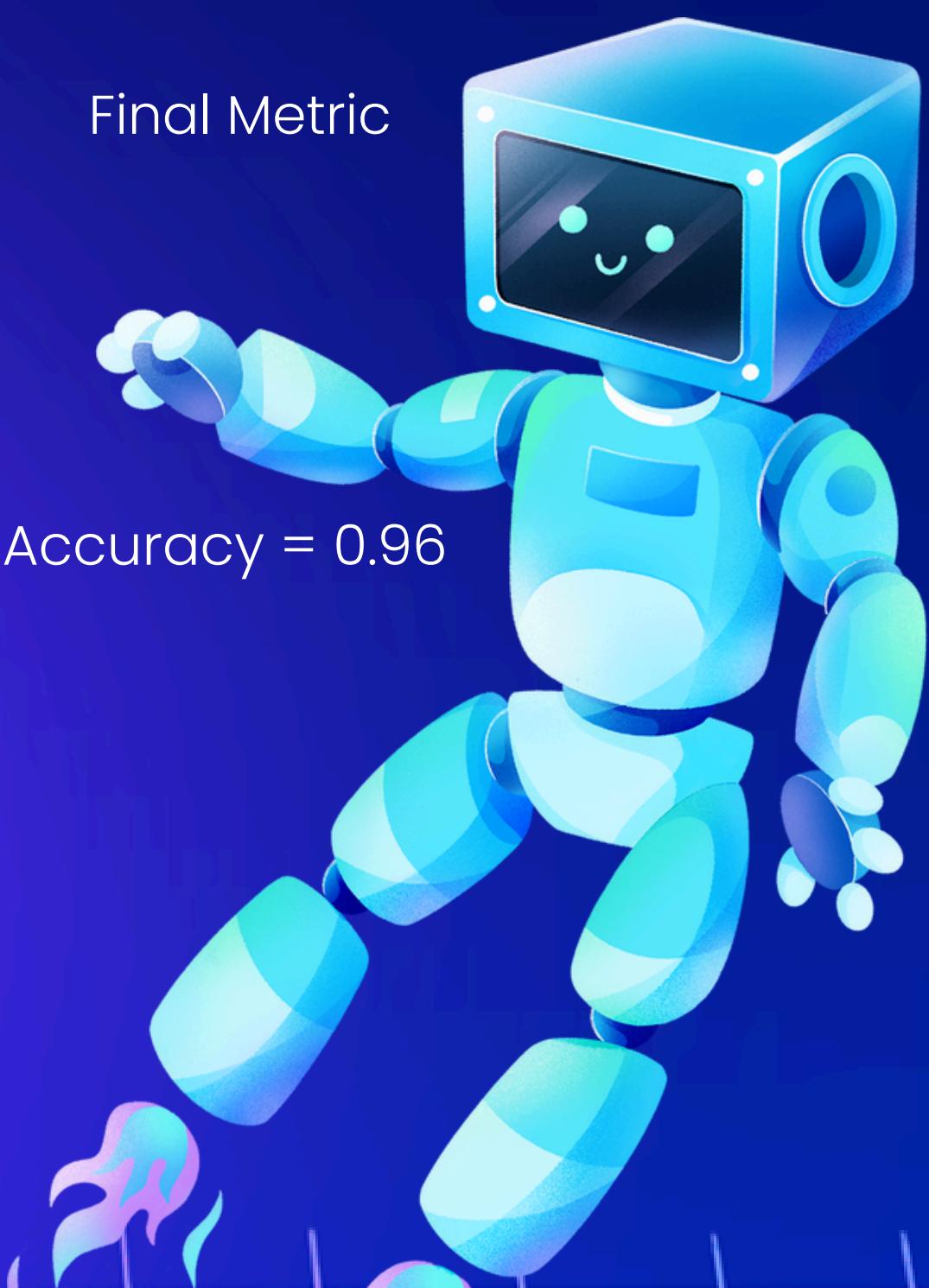
Final Metric

LSTM MODEL

MIT-BIH Arrhythmia  
Dataset

Epoch=150

Accuracy = 0.96



# LSTM PREFERENCE

## LSTM

- ✓ Best for long sequences (3-gate mechanism handles 30-min ECGs)
- ✓ Highest accuracy (96.5%) on MIT-BIH
- ✓ Robust to noise/missing data

## GRU

~1-2% lower accuracy than LSTM

Faster training but struggles with very long-term dependencies

- ✗ 2-gate design may miss subtle ECG patterns

## CNN

Requires hybrid (CNN-LSTM) for good results

Alone, fails to model temporal relationships (RR intervals, P-QRS-T timing)

- ✗ Fixed-length inputs needed (pads/truncates ECGs)
- ✗ Blind to long-range rhythms

# THANK YOU !

