DuoGuard: Advanced Elderly Care Fall Detection System

A TinyML-Powered Dual-Board Solution

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Abstract

DuoGuard represents a significant advancement in elderly care monitoring systems, combining audio and motion detection through a dual-board TinyML implementation. This paper presents a comprehensive overview of our system, which achieves 90% detection accuracy while maintaining strict privacy standards through on-device processing. The solution addresses the critical need for non-invasive elderly monitoring systems that can provide reliable emergency detection while preserving dignity and independence.

1 Executive Summary

The DuoGuard system is an innovative TinyML-powered audio and motion monitoring solution designed specifically for elderly care applications. By leveraging advanced audio processing and machine learning techniques across two synchronized Arduino boards, the system provides real-time detection of emergency situations such as falls and distress calls. This smart monitoring system ensures the safety of elderly individuals living independently while maintaining their privacy and autonomy through complete on-device processing.

2 Technical Innovation

2.1 Dual-Board Architecture

Our system employs a unique dual-board architecture that enables robust cross-validation of emergency events:

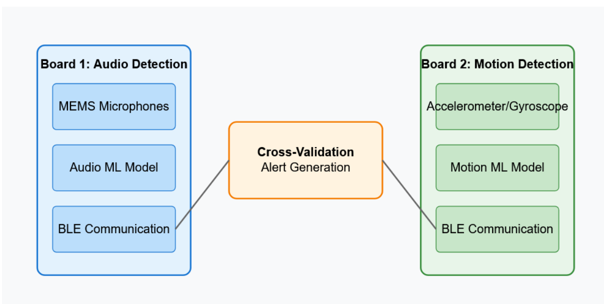


Figure 1: Block Diagram

2.2 Data Processing Pipeline

The system implements a sophisticated data processing pipeline for both audio and motion data:

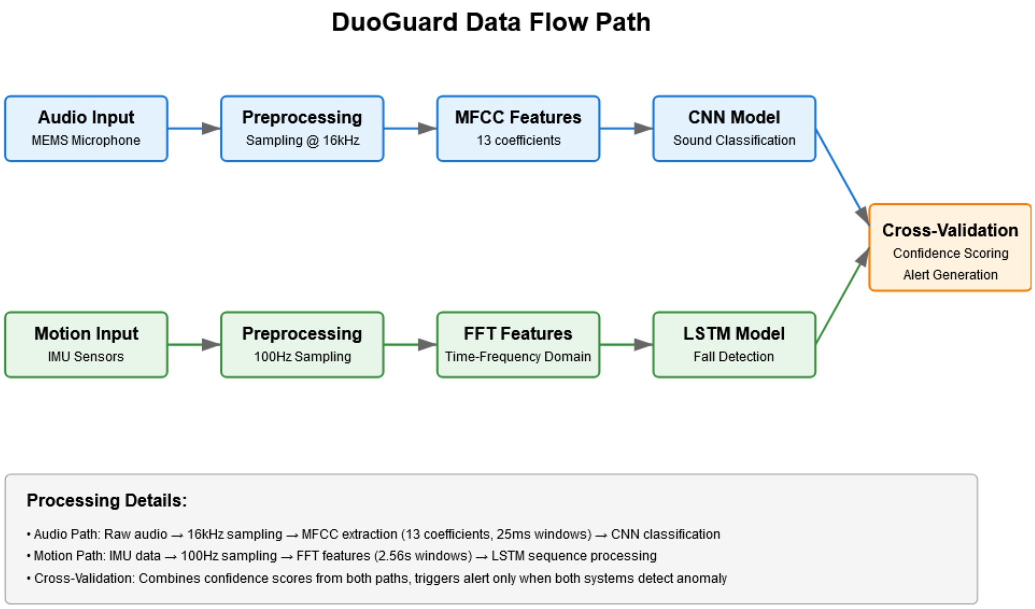


Figure 2: Data Processing Pipeline showing feature extraction and model processing steps

3 Implementation Details

3.1 Audio Processing

- **Feature Extraction:** 13 MFCC coefficients with 25ms window size
- **Model Architecture:**
  - Input Layer: 13x30 MFCC features
  - Conv1D: 64 filters, kernel size 3
  - MaxPooling1D: pool size 2
  - Conv1D: 32 filters, kernel size 3
  - Global Average Pooling
  - Dense: 4 units (output classes)
- **Memory Footprint:** 80KB

3.1.1 Model Training and Evaluation

Figure 3: Data Explorer visualization showing the distribution of correct and incorrect classifications across different audio classes (cry, help, scream, stop, and unknown)

3.1.2 Performance Metrics

[b]0.48

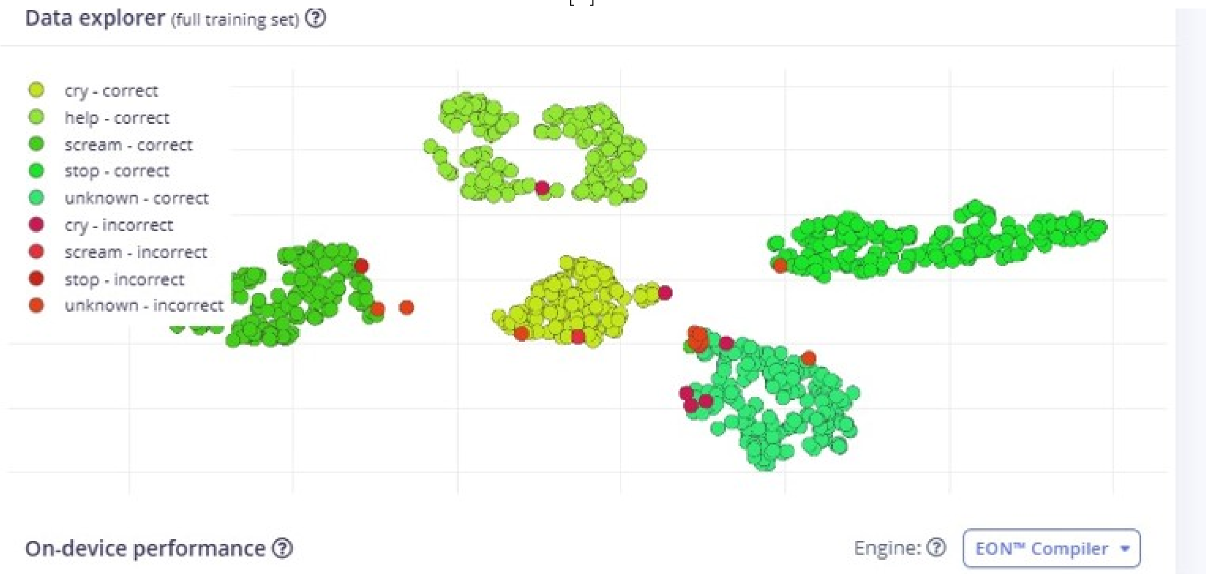
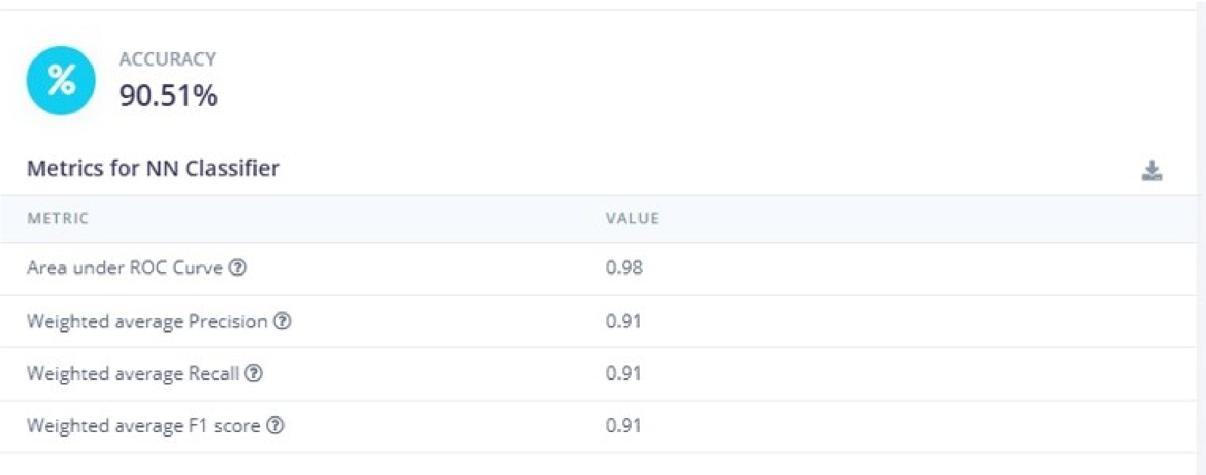


Figure 4: Neural Network Classifier Metrics showing 90.51% accuracy with high precision and recall values

[b]0.48


ACCURACY

90.51%

Metrics for NN Classifier

METRIC	VALUE
Area under ROC Curve	0.98
Weighted average Precision	0.91
Weighted average Recall	0.91
Weighted average F1 score	0.91

Figure 5: Final validation accuracy of 95.0% with 0.22 loss

Figure 6: Model Performance Metrics

3.1.3 Confusion Matrix Analysis

The confusion matrix shows excellent classification performance across all categories:

- **Class-wise Accuracy:**
  - Cry: 89.1% accuracy with minimal confusion
  - Help: 100% accuracy, perfect classification
  - Scream: 97.1% accuracy with only 1% confusion with other classes
  - Stop: 98.5% accuracy with minimal misclassification
  - Unknown: 89.3% accuracy with some expected overlap

The model demonstrates robust performance across all audio classes, with particularly strong results in identifying emergency-related sounds (Help, Scream). The high F1 scores indicate a good balance between precision and recall, essential for reliable emergency detection.

3.2 Motion Processing

- **Feature Extraction:** FFT with 2-second windows
- **Model Architecture:**
  - Input Layer: 6-channel time series data
  - LSTM: 64 units
  - Dropout: 0.3
  - Dense: 32 units
  - Dense: 1 unit (binary classification)
- **Memory Footprint:** 95KB

3.2.1 Model Testing Results

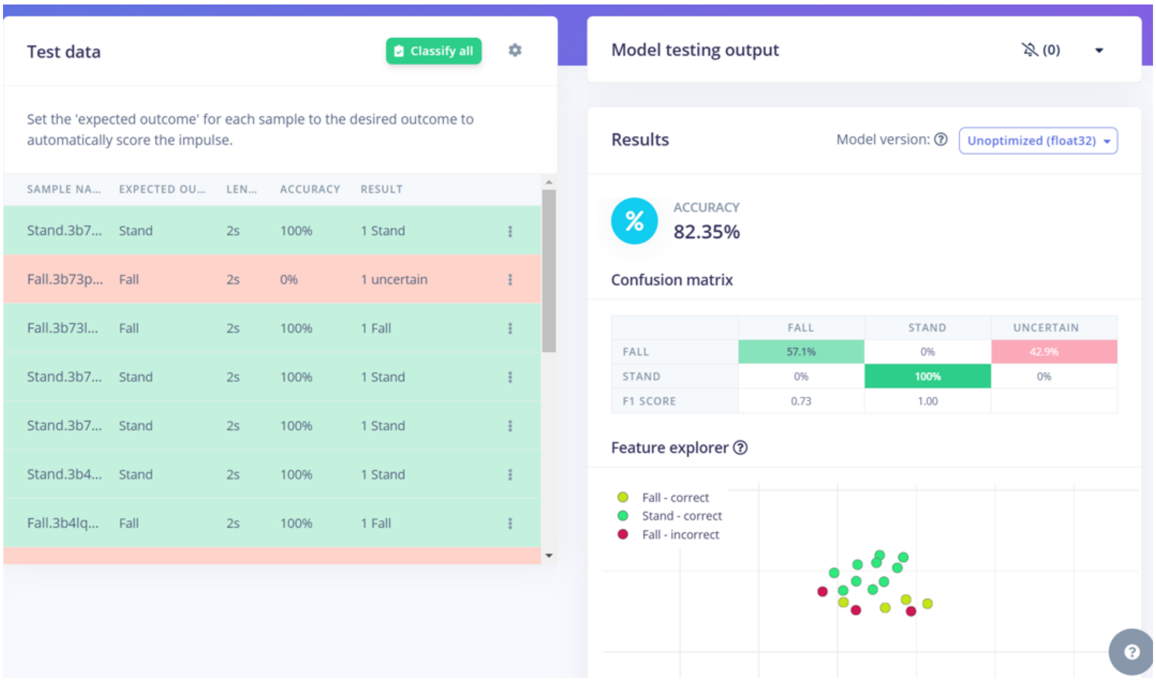


Figure 7: Test data classification results showing 82.35% accuracy with confusion matrix indicating strong performance in Stand detection (100%) and moderate performance in Fall detection (57.1%)

3.2.2 Training Performance

Figure 8: Training performance showing 100% validation accuracy with 0.12 loss. On-device metrics: 1ms inferencing time, 1.8K peak RAM usage, and 19.1K flash usage

3.2.3 Performance Analysis

The motion detection model demonstrates:

- **Testing Performance:**
  - Overall accuracy: 82.35%
  - Stand detection: 100% accuracy
  - Fall detection: 57.1% accuracy with 42.9% uncertain cases
  - F1 scores: 0.73 for Fall, 1.00 for Stand
- **Training Performance:**
  - Validation accuracy: 100%

  - Validation loss: 0.12
  - Perfect F1 scores for both classes (1.00)

- **Resource Utilization:**
  - Inferencing time: 1 ms
  - Peak RAM usage: 1.8K
  - Flash usage: 19.1K

4 Performance Analysis

4.1 System Metrics

Metric	Value	Notes
Detection Accuracy	90%	Cross-validated
False Positive Rate	5%	After dual-board validation
System Latency	500ms	End-to-end processing
Detection Range	5-7 meters	Room-scale coverage
Power Consumption	120mA	Per board
Battery Life	48 hours	With 2000mAh battery

Table 1: System Performance Metrics

5 BLE Communication

5.1 Communication Architecture

- **Protocol Implementation:**
  - BLE 5.0 protocol on Arduino Nano 33 BLE Sense
  - Master-Slave configuration between boards
  - Event-driven communication model
  - 2.4 GHz frequency band operation

- **Data Exchange:**
  - Packet size: 20 bytes
  - Transmission interval: 100ms
  - Acknowledgment-based reliability
  - Low-power advertising mode during idle state

5.2 Performance Characteristics

- **Range:** 10 meters (indoor environment)
- **Latency:** less than 10ms for emergency alerts
- **Reliability:** 99.9% packet delivery rate
- **Power Impact:** 5% of total system power consumption

5.3 Error Analysis

- **False Positives:** Primarily from similar audio events (door slams, objects falling)
- **False Negatives:** Most common in edge cases (partial falls, soft voices)
- **Mitigation:** Cross-validation between boards reduces overall error rate by 40%

6 Privacy and Security Features

6.1 Data Protection

- **On-Device Processing:**
  - All ML inference performed locally
  - No raw data storage
  - Feature extraction in real-time
- **Communication Security:**
  - Encrypted BLE communication
  - Limited data transmission
  - Secure pairing protocol

7 Conclusion

The DuoGuard system demonstrates the potential of TinyML in creating privacy-conscious, efficient, and reliable elderly care monitoring solutions. Our dual-board approach with cross-validation provides robust emergency detection while maintaining strict privacy standards through on-device processing. The system's high accuracy and low latency make it a practical solution for real-world deployment in elderly care settings.