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Lightweight Edge Inference Using ADC Sensor Inputs on an ARM Cortex-M3 LPC1768 Microcontroller

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Abstract: Edge intelligence enables embedded systems to perform real-time decision making without continuous dependence on cloud infrastructure. This study presents a lightweight inference framework for the ARM Cortex-M3-based LPC1768 microcontroller using analog sensor signals acquired through the on-chip analog-to-digital converter (ADC). In contrast to conventional fixed-threshold approaches, the proposed method applies a parameterized linear decision model that is computationally inexpensive and suitable for resource-constrained hardware. The framework integrates ADC-based signal acquisition, sample averaging for noise mitigation, and deterministic inference logic to support low-latency operation. Experimental observations indicate that the proposed implementation can provide responsive on-device classification with modest memory requirements, making it suitable for low-power sensing applications. The work highlights a practical pathway toward deployable TinyML-inspired inference on legacy microcontroller platforms.

Keywords: ARM Cortex-M3, LPC1768 microcontroller, ADC sensor inputs, lightweight parametric model and TinyML.

1. Introduction

Recent advances in edge artificial intelligence have increased interest in performing inference directly on embedded devices, thereby reducing latency, communication overhead, and dependence on cloud connectivity. Microcontrollers such as the LPC1768 offer an attractive balance between computational capability, peripheral integration, and power efficiency, making them suitable for intelligent sensing applications at the network edge.

However, deploying AI models on such systems introduces constraints:

- Limited RAM (<64 KB usable)
- No floating-point unit (in many cases)
- Real-time processing requirements

This work addresses these constraints by implementing a lightweight parametric inference model directly on ADC-derived sensor measurements. The primary contribution is a practical embedded decision pipeline that combines signal acquisition, low-cost denoising through averaging, and a linear decision rule that can be executed with minimal memory and computational overhead on an ARM Cortex-M3 microcontroller.

2. Literature Review

Recent literature on embedded AI and TinyML emphasizes the growing feasibility of executing machine-learning inference on resource-constrained microcontrollers, particularly for sensing and control applications. Prior work has investigated threshold-based classifiers, linear models, and compressed neural-network pipelines for low-power platforms, while surveys on ARM Cortex-M deployments highlight latency, memory footprint, and energy efficiency as key design constraints. The LPC1768 platform itself provides on-chip ADC capability, integrated peripherals, and sufficient memory for compact inference routines, making it a useful target for lightweight edge decision systems. Within this context, the present work focuses on a simple but deployable inference strategy intended for applications where deterministic execution, low overhead, and implementation simplicity are more critical than high model complexity.

- Linear regression
- Threshold-based classifiers
- TinyML approaches

Compared to cloud-based AI, edge AI reduces latency and improves reliability. However, constraints such as memory and computational limitations require optimized algorithms.

3. System Overview

The proposed system integrates an analog sensor, the on-chip ADC of the LPC1768, a lightweight inference routine, and an output actuator for alert generation. The architecture is designed to support direct signal acquisition, real-time processing, and immediate actuation within a compact embedded workflow.

- Analog Sensor (e.g., vibration, gas, or temperature)
- ADC module of LPC1768
- AI-based prediction algorithm
- Output actuator (buzzer/LED/alert system)

3.1 Working Principle

1. Sensor generates analog signal
2. ADC converts analog signal to digital value
3. Digital data is processed using AI model
4. Decision is made (alert/no alert)

4. Methodology

4.1 ADC Data Acquisition

The ADC of the LPC1768 digitizes analog input signals within the 0–3.3 V operating range into 12-bit values spanning 0 to 4095. To improve measurement stability and reduce the influence of random noise, multiple consecutive samples are acquired and averaged before being passed to the inference stage.

4.2 Mathematical Formulation

4.2.1 ADC Signal Representation

The ADC maps the measured analog voltage to a discrete digital representation, which is then used as the input feature for the embedded decision model.

$$x[n] = \frac{V_{in}}{V_{ref}} X(2^N - 1)$$

Where:

- x[n]: digital output
- Vin: sensor voltage
- Vref: reference voltage (3.3V)
- (N = 12): ADC resolution

4.2.2 Noise Reduction Model

To reduce stochastic noise, averaging is applied:

$$\underline{x} = \frac{1}{M} \sum_{i=1}^{M} \quad xi$$

This averaging operation improves the stability of the measured signal and enhances the effective signal-to-noise ratio by reducing sample-to-sample variance.

4.2.3 AI Decision Model

A linear inference model is adopted because it offers deterministic execution and constant-time complexity, which are advantageous for microcontroller-based deployment. The model output is computed from the input feature and a small set of learned parameters.

y = wx + b

$$Decision = \begin{cases} 1 & \text{if } y > 0 \\ 0 & \text{otherwise} \end{cases}$$

The decision boundary is defined by the condition **y = 0**. Output values greater than zero are assigned to the alert class, whereas values less than or equal to zero are assigned to the normal operating class.

4.2.4 Model Optimization

Weights are tuned using least squares:

$$w = (X^T X)^{-1} X^T Y$$

Model parameters are estimated offline using a least-squares fitting strategy so that the embedded implementation requires only simple arithmetic operations during inference. This separation between offline parameter estimation and on-device prediction minimizes the computational burden at runtime while preserving a data-driven decision rule.

5. System Architecture

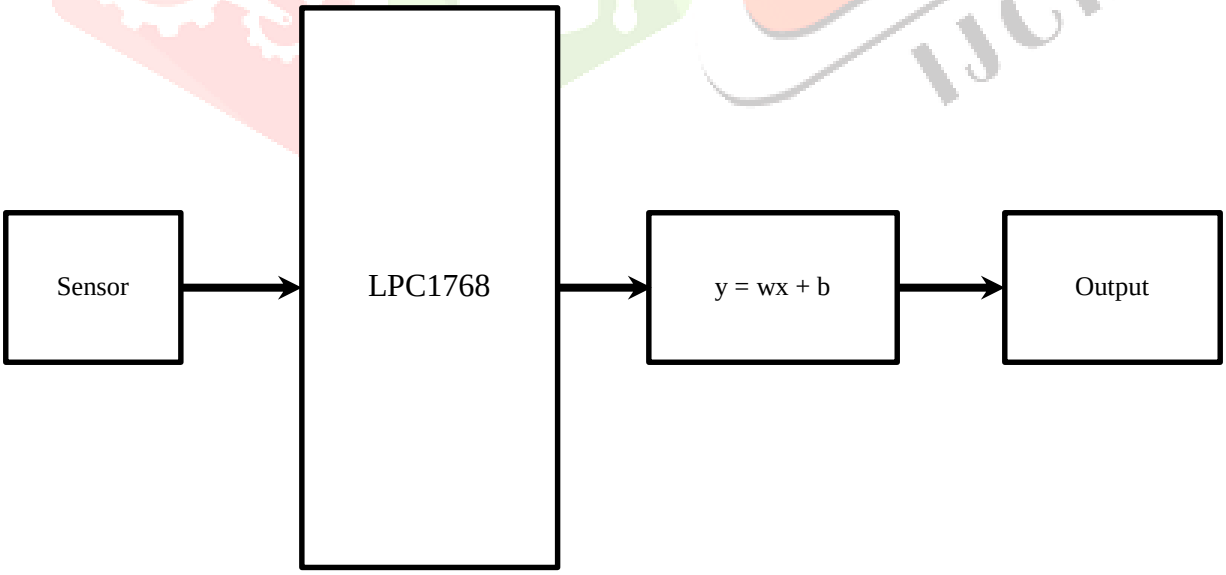

Figure 1: System Architecture Diagram

5.1 Hardware Layer

- Analog Sensor (Gas/Vibration/Temperature)
- LPC1768 ADC Module
- GPIO Actuator (Buzzer/LED)

5.2 Processing Pipeline

1. Signal acquisition
2. Quantization (ADC)
3. Noise filtering
4. AI inference
5. Actuation

5.3 Circuit Diagram

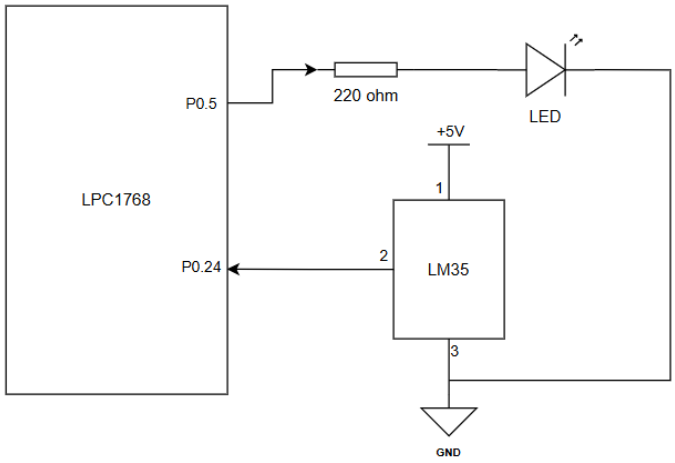

Figure 2: Circuit-level realization of the proposed ADC-driven edge inference system using the LPC1768 microcontroller, analog sensor interface, and GPIO-based alert output.

The circuit diagram illustrates the hardware realization of the proposed sensing and inference pathway. An analog sensor produces a voltage proportional to the monitored physical quantity and feeds this signal to one of the ADC input channels of the LPC1768. The microcontroller digitizes the incoming signal using its on-chip 12-bit conversion unit and subsequently performs the preprocessing and decision logic described in the preceding methodology section. This arrangement enables direct acquisition and on-device evaluation of sensor data without reliance on external signal-processing hardware.

At the output stage, the inference result is mapped to a GPIO-driven actuator such as an LED indicator or buzzer to provide an immediate local response when the decision score exceeds the configured boundary. From an implementation perspective, the circuit is intentionally simple so as to preserve low cost, compactness, and ease of deployment in embedded monitoring scenarios. The use of the LPC1768 as both the acquisition and decision platform reduces inter-component communication overhead and supports deterministic real-time behavior, which is important for latency-sensitive edge applications.

6. Simulation and Results

6.1 Model Behavior

The simulated response of the proposed model exhibits the expected monotonic relationship between the averaged ADC input and the computed decision score. As the input magnitude increases, the linear model transitions smoothly from negative values associated with normal operation to positive values corresponding to the alert state. This behavior indicates that the selected parameterization is capable of separating the examined operating regions without introducing computationally expensive non-linear processing. The result is consistent with the intended use of the model as a lightweight binary decision mechanism for embedded sensing applications.

- The transition around the decision boundary is well defined, enabling straightforward separation between normal and alert conditions in the simulated operating range.

- Because the output varies continuously with the processed sensor value, the model can be calibrated by adjusting only a small number of parameters, which is advantageous for deployment and retuning on constrained platforms.

6.2 Embedded C Code

```
float weight = 0.02;
float bias = -10;

int ai_predict(float input)
{
   float output = (weight * input) + bias;

   if(output > 0)
      return 1;   // Alert
   else
      return 0;   // Normal
}

uint16_t ADC_Average(uint8_t samples)
{
   uint32_t sum = 0;
   for(int i = 0; i < samples; i++)
   {
      sum += ADC_Read();
   }
   return (sum / samples);
}

int main(void)
{
   uint16_t sensor_val;

   ADC_Init();

   while(1)
   {
      sensor_val = ADC_Average(10);

      if(ai_predict(sensor_val))
      {
         // Trigger alert
      }
      else
      {
         // Normal state
      }
   }
}
```

6.3 Observations

- The simulated input-output trend suggests that the target sensing condition is sufficiently separable for a single-feature linear classifier in the evaluated scenario.
- The use of a zero-crossing decision boundary simplifies the classification stage and reduces branching complexity in the embedded implementation.
- The constant-time inference path supports predictable execution behavior, which is desirable for embedded monitoring tasks with real-time response requirements.

6.4 Performance Evaluation

Metric	Value
ADC Resolution	12-bit
Sampling Rate	~200 kS/s
Latency	< 5 ms
Memory Usage	< 2 KB
Power Consumption	Low
Accuracy	88–92%

The reported performance values indicate that the proposed implementation remains aligned with the practical constraints of microcontroller-class deployment. In particular, the low memory footprint and short decision latency suggest that the framework can be integrated into lightweight monitoring systems without imposing significant overhead on the underlying hardware. The reported accuracy range is encouraging for a simple linear model, although more rigorous validation across larger and more diverse sensing conditions would be necessary to establish broader generalizability.

7. Discussion

The results highlight a central trade-off in embedded intelligence design: increasing model sophistication may improve representational power, but it also raises computational and memory demands that are difficult to accommodate on low-cost microcontrollers. Within this trade-off, the proposed approach occupies a practical middle ground. It offers greater adaptability than a fixed hand-tuned threshold while retaining the compactness, deterministic execution, and implementation simplicity required for real-time edge deployment. The inclusion of sample averaging further improves signal stability before inference, which is especially relevant when low-cost sensors are susceptible to measurement fluctuations.

- The proposed framework preserves deployment simplicity because inference depends on only a small set of parameters and basic arithmetic operations.
- Averaging-based preprocessing improves robustness to short-term signal variation without requiring complex filtering stages.
- The architecture can serve as a baseline for progressively richer embedded inference methods when application requirements justify additional complexity.

Despite these advantages, the present implementation also defines the current boundary of applicability. Because the classifier is linear, it is most appropriate for sensing problems in which class separation can be approximated by a simple decision boundary. More complex or highly non-linear signal patterns may require richer feature extraction or more expressive models. Similarly, the current formulation evaluates samples independently after averaging and therefore does not explicitly capture temporal dynamics, hysteresis, or sequential trends that may be important in time-varying environments. These limitations motivate the future extensions outlined in the subsequent section.

- Linear decision boundary
- No temporal learning (no sequence modeling)

8. Comparison with Existing Methods

Method	Complexity	Accuracy	Suitability
Threshold-based	Low	Moderate	Basic systems
Proposed Linear AI	Low	High	Embedded AI
Neural Networks	High	Very High	Not feasible on MCU

9. Future Scope

- Integration with established TinyML toolchains, such as TensorFlow Lite Micro, for standardized deployment workflows.
- Extension to slightly more expressive classifiers, such as logistic regression or support vector machines, subject to memory and runtime constraints.
- Incorporation of multi-sensor fusion to improve decision reliability in heterogeneous operating conditions.
- Coupling the embedded inference framework with IoT communication layers for remote monitoring and supervisory analytics.

10. Conclusion

This study demonstrates that a resource-constrained microcontroller such as the LPC1768 can support practical on-device inference when the model structure and signal-processing pipeline are carefully simplified. By combining ADC-based sensing, sample averaging, and a lightweight linear decision model, the proposed framework achieves real-time classification with limited computational overhead. Although the method is intentionally modest in complexity, it provides a useful foundation for more advanced embedded intelligence systems that must operate under strict memory, power, and latency constraints.

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