A NOVEL FRAMEWORK FOR REAL-TIME AERODYNAMIC PRECURSOR DETECTION OF CLEAR-AIR TURBULENCE (CAT) USING MEMS SENSOR ARRAYS AND EDGE ARTIFICIAL INTELLIGENCE

By

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DECLARATION OF AUTHORSHIP

I, Houssam Rharbi, state that this thesis and the work presented are my own, completed independently and without institutional enrolment.

I have acknowledged all main sources of help.

Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

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ABSTRACT

Clear-Air Turbulence (CAT) remains one of the most insidious hazards in modern civil aviation, characterized by its invisibility to conventional Doppler radar systems that rely on precipitation reflectivity. As global air traffic density increases and climate change intensifies upper-atmospheric shear instabilities, the need for a robust, onboard detection mechanism has become critical. This research proposes a paradigm shift from reactive mitigation (Pilot Reports) to predictive sensing.

We present the design, development, and validation of a "Smart Skin" system—a surface-mounted sensor array capable of detecting the minute aerodynamic pressure fluctuations that precede the breakdown of laminar flow into turbulence. The proposed system leverages the fusion of high-precision MEMS barometers (Bosch BMP388) and 6-axis Inertial Measurement Units (MPU-6050) to isolate aerodynamic anomalies from engine-induced vibration.

The signal processing pipeline utilizes a quantized 1D Convolutional Neural Network (1D-CNN) deployed on an Arduino Nicla Vision microcontroller. This "Edge AI" approach eliminates cloud latency, achieving an inference time of under 60 milliseconds. Experimental validation in a simulated wind-tunnel environment demonstrates a prediction accuracy of 88.5%, providing a safety-critical warning window of 2 to 3 seconds before major vertical acceleration occurs.

The findings suggest that low-cost, distributed sensor networks can effectively complement existing LIDAR-based solutions, offering a scalable path toward safer skies.

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NOMENCLATURE

CAT	Clear-Air Turbulence
CNN	Convolutional Neural Network
DAQ	Data Acquisition
FFT	Fast Fourier Transform
IMU	Inertial Measurement Unit
KHI	Kelvin-Helmholtz Instability
LIDAR	Light Detection and Ranging
MEMS	Micro-Electro-Mechanical Systems
NTSB	National Transportation Safety Board
PIREP	Pilot Report
PSD	Power Spectral Density
Re	Reynolds Number
Ri	Richardson Number
SNR	Signal-to-Noise Ratio
TFLM	TensorFlow Lite for Microcontrollers

CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

Since the inception of commercial aviation, atmospheric turbulence has posed a persistent threat to the safety and comfort of air travel. While modern meteorology and avionics have largely conquered the dangers of convective storms through the use of X-band weather radar, Clear-Air Turbulence (CAT) remains an invisible and unpredictable hazard. Occurring in cloudless skies, typically at cruising altitudes between 30,000 and 40,000 feet, CAT is often associated with the strong wind shears found in the jet stream.

The inability of current onboard systems to detect CAT means that pilots must rely on forecasting charts, which are often hours old, or Pilot Reports (PIREPs) from other aircraft. This reactive approach creates a systemic vulnerability: the first aircraft to fly through a turbulent sector acts as a probe, often suffering severe structural loading and passenger injuries, before a warning can be issued to trailing aircraft.

Recent data from the National Transportation Safety Board (NTSB) highlights that turbulence is the leading cause of non-fatal injuries in commercial aviation. With the projected growth in global air traffic and the potential for climate change to intensify the jet stream, the frequency of severe CAT encounters is expected to rise. This creates an urgent operational imperative for a predictive, real-time detection system.

This dissertation explores a novel solution to this problem: the use of a "Smart Skin" sensor array. By embedding high-sensitivity pressure sensors directly onto the aircraft fuselage, we aim to detect the infrasonic pressure precursors generated by the onset of Kelvin-Helmholtz Instability, the physical mechanism driving CAT.

1.2 The Economic and Safety Impact

The consequences of turbulence extend beyond safety to significant economic impacts. For major airlines, turbulence-related costs are estimated to exceed $500 million annually in the United States alone. These costs arise from three primary sources: injury compensation, aircraft maintenance, and operational inefficiencies.

Injuries to passengers and crew often occur when the aircraft experiences sudden vertical accelerations, throwing unbuckled individuals against the cabin structure. These incidents result in costly medical claims, legal settlements, and lost work time for flight crew. Furthermore, the psychological impact on passengers contributes to a fear of flying, indirectly affecting revenue.

Structurally, severe turbulence encounters necessitate mandatory "hard landing" or "severe turbulence" inspections. These maintenance procedures require the aircraft to be grounded, often for several days, while technicians perform non-destructive testing (NDT) on critical load-bearing components such as the wing roots and engine pylons. The loss of revenue from a grounded airframe is substantial.

Operationally, pilots often request altitude changes or course deviations to avoid reported turbulence. These deviations are rarely optimal for fuel consumption. A descent of 4,000 feet to find smoother air increases air density and drag, significantly increasing fuel burn. A system that could pinpoint the exact location of turbulence would allow for more precise, efficient flight path adjustments.

1.3 Problem Statement

The central engineering challenge addressed in this work is the detection of aerodynamic precursors in a high-noise environment using resource-constrained hardware. The signal of interest—a pressure fluctuation of 5 to 10 Pascals at 2-5 Hz—is orders of magnitude weaker than the background noise generated by the engines and the turbulent boundary layer.

Current detection methods, such as LIDAR, are effective but prohibitively expensive, heavy, and power-hungry for widespread fleet adoption. Conversely, accelerometer-based systems are cheap but reactive; they detect turbulence only after the aircraft has already entered it.

Furthermore, processing high-frequency sensor data requires significant computational power. Traditional signal processing techniques like the Fast Fourier Transform (FFT) introduce latency due to buffering requirements. In a flight safety context, a delay of even two seconds can render a warning useless. Therefore, a solution is needed that combines the sensitivity of remote sensing with the low cost of MEMS technology and the speed of Edge Computing.

The research question driving this dissertation is:

Can a low-power, machine-learning algorithm running on a microcontroller distinguish between the specific signature of aerodynamic instability and the background noise of normal flight in real-time?

1.4 Research Objectives

To address the problem statement, this dissertation pursues the following specific objectives:

Hardware Engineering: To design and prototype a Data Acquisition (DAQ) node using the Bosch BMP388 high-precision barometer and the Arduino Nicla Vision. This involves optimizing the I2C bus communication for maximum throughput and designing a power-efficient circuit suitable for embedded deployment.

Algorithm Development: To develop a signal processing pipeline that can normalize sensor data in real-time, removing altitude-induced drift while preserving high-frequency aerodynamic features.

Neural Network Design: To design and train a 1D Convolutional Neural Network (CNN) capable of classifying flow regimes (Laminar vs. Turbulent) based on temporal pressure patterns.

Edge Implementation: To deploy the trained model onto the microcontroller using TensorFlow Lite for Microcontrollers (TFLM), utilizing quantization to fit the model within the device's limited memory constraints.

Validation: To validate the system's performance in a controlled wind tunnel environment, measuring accuracy, recall, and inference latency.

CHAPTER 2: LITERATURE REVIEW

2.1 Atmospheric Physics of CAT

Clear-Air Turbulence is not a random chaotic event but the result of specific fluid dynamic instabilities. The primary driver of CAT is the Kelvin-Helmholtz Instability (KHI). This phenomenon occurs when there is a velocity shear in a single continuous fluid, or where there is a velocity difference across the interface between two fluids.

In the atmosphere, this shear is most prominent in the jet stream—a narrow band of strong winds in the upper troposphere. The boundary between the fast-moving core of the jet stream and the slower surrounding air creates a region of intense shear. When this shear force exceeds the stabilizing force of atmospheric stratification (buoyancy), the flow becomes unstable.

The evolution of KHI follows a predictable pattern. Initially, small perturbations in the flow grow into organized waves, known as gravity waves. These waves can have wavelengths ranging from hundreds of meters to several kilometers. As they grow in amplitude, they eventually "break," much like ocean waves on a beach, collapsing into chaotic, turbulent eddies. It is this breakdown phase that causes the violent buffeting experienced by aircraft.

Research by Sharman and Lane (2016) suggests that the "precursor" phase—the growth of the gravity waves—can last for tens of seconds to minutes before the turbulent breakdown occurs. Detecting the pressure signature of these waves offers a potential early warning system.

2.2 Kelvin-Helmholtz Instability Mechanics

The mathematical condition for the onset of KHI is governed by the Richardson Number (Ri). The Richardson Number is a dimensionless ratio that compares the potential energy of the fluid's stratification to the kinetic energy of the shear.

Mathematically, it is expressed as:

$$Ri = (g / \theta)*(\partial\theta/\partial z) / (\partial u/\partial z)^2$$

Where g is gravity, θ is potential temperature, z is height, and u is horizontal wind speed. The numerator represents the stability of the atmosphere (stratification), while the denominator represents the strength of the wind shear.

The Miles-Howard theorem states that a necessary condition for instability is that $Ri < 0.25$ somewhere in the flow. When Ri drops below this critical quarter, the stabilizing effect of gravity is insufficient to prevent the shear from overturning the fluid. This theoretical threshold is crucial for our detection algorithm, as it defines the boundary conditions under which we expect to see precursor waves.

In practice, measuring the Richardson Number directly from an aircraft is difficult because it requires knowledge of the wind and temperature profiles *above and below* the aircraft, which onboard sensors cannot measure. However, the pressure fluctuations resulting from the instability *can* be measured on the skin of the aircraft.

2.3 Existing Detection Technologies

Historically, various technologies have been proposed for CAT detection, each with significant limitations.

Infrared Radiometry: In the 1970s, researchers experimented with Forward-Looking Infrared (FLIR) sensors to detect temperature gradients associated with CAT. The theory was that shear layers often coincide with temperature inversions. However, this method suffered from high false alarm rates, as not all temperature gradients result in turbulence, and humidity could interfere with the readings.

Doppler LIDAR: Light Detection and Ranging (LIDAR) is currently the gold standard for remote turbulence detection. By emitting laser pulses and measuring the Doppler shift of the light reflected off aerosols (dust particles) in the air, LIDAR can accurately map the wind velocity field ahead of the aircraft.

While effective, LIDAR systems are heavy, expensive (costing hundreds of thousands of dollars), and power-hungry. They also struggle in extremely clean air at high altitudes where aerosol concentration is low.

Accelerometers: The most common "detection" method today is actually a reporting method. Aircraft are equipped with accelerometers that measure the G-load. Algorithms like the Vertical Gust Load (VGL) or Eddy Dissipation Rate (EDR) use this data to quantify turbulence severity. However, this data is only generated *after* the aircraft is shaking, making it useful for trailing aircraft but useless for the aircraft generating the report.

2.4 Machine Learning in Avionics

The integration of Machine Learning (ML) into safety-critical avionics is a relatively new frontier. Traditionally, avionics software is deterministic, following strict logic paths verified under standards like DO-178C. Probabilistic models like Neural Networks introduce a layer of uncertainty that regulators are cautious about.

However, the sheer complexity of aerodynamic noise makes deterministic algorithms insufficient for early turbulence detection. Simple threshold-based triggers result in too many false positives from pilot maneuvers or engine vibrations. ML offers the ability to learn complex, non-linear patterns in the data.

Recent advances in "TinyML"—running ML models on microcontrollers—have opened new possibilities. Frameworks like TensorFlow Lite for Microcontrollers allow engineers to train models on powerful workstations and then compress (quantize) them to run on chips with only kilobytes of RAM. This enables "Smart Sensors" that can process data locally without needing to transmit high-bandwidth raw data to a central computer.

This dissertation builds upon this trend, proposing a decentralized architecture where the intelligence resides on the sensor node itself.

CHAPTER 3: THEORETICAL FRAMEWORK

3.1 Fluid Dynamics Equations

To understand what our sensors are detecting, we must look at the governing equations of fluid motion. The Navier-Stokes equations describe the motion of viscous fluid substances. For the high-altitude, high-speed regime of commercial flight, we are interested in the unsteady pressure term.

The relationship between velocity fluctuations and pressure fluctuations in a turbulent flow is often approximated by the Unsteady Bernoulli Equation. For an incompressible, inviscid flow, the pressure fluctuation p' is related to the velocity fluctuation u' by:

```
p' ≈ -ρ *U*u'
```

Where ρ is the air density and U is the mean free-stream velocity. This linear relationship implies that a velocity perturbation in the atmosphere (a gust) will manifest as a pressure perturbation on the aircraft skin.

At a cruising altitude of 35,000 feet, the air density ρ is approximately 0.38 kg/m^3, and the velocity U is roughly 250 m/s. A vertical gust u' of just 1 m/s (light turbulence) would therefore generate a pressure fluctuation on the order of 95 Pascals. This is well within the dynamic range of modern MEMS sensors, provided the noise floor is sufficiently low.

3.2 Aerodynamic Acoustics and Pseudo-Sound

A major challenge in this research is distinguishing the "true" pressure signal from the atmosphere from the "self-noise" of the aircraft. As an aircraft moves through the air, a turbulent boundary layer forms on the surface of the fuselage. The turbulent eddies within this boundary layer create pressure fluctuations on the skin.

This phenomenon is known as "pseudo-sound." It is termed "pseudo" because, unlike a true acoustic wave that propagates at the speed of sound, these pressure fluctuations convect at the speed of the flow. Ideally, our sensor would measure the pressure of the free stream, unaffected by the boundary layer.

However, surface-mounted sensors are inevitably immersed in the boundary layer. The spectral characteristics of boundary layer noise are typically broadband and high-frequency, scaling with the flow velocity. In contrast, the Kelvin-Helmholtz waves we seek to detect are large-scale structures with low frequencies (below 5 Hz). This spectral separation is the key that allows us to filter out the noise. Our Neural Network is essentially trained to look for high-energy, low-frequency patterns that stand out against the high-frequency background hiss of the boundary layer.

CHAPTER 4: HARDWARE DESIGN

4.1 Microcontroller Selection

The selection of the microcontroller unit (MCU) was driven by the need for a balance between computational performance and power efficiency. The system needs to sample data at a high rate, perform signal processing, and run a neural network inference, all within a strict power budget.

We selected the **Arduino Nicla Vision** board. This board features the STM32H747XI, a dual-core microcontroller containing a Cortex-M7 core running at 480 MHz and a Cortex-M4 core running at 240 MHz. This heterogeneous architecture is ideal for our application:

Cortex-M7: This high-performance core is dedicated to running the TensorFlow Lite interpreter. It handles the matrix multiplications and activation functions of the CNN. The M7 core includes a double-precision Floating Point Unit (FPU) and DSP instructions, accelerating the mathematical operations.

Cortex-M4: This core serves as a co-processor for I/O operations. It manages the I2C bus communication with the sensors, handles interrupts, and manages the data buffers. By offloading these tasks to the M4, we ensure that the M7 is never blocked waiting for sensor data, maximizing the inference throughput.

The Nicla Vision also includes a Power Management IC (PMIC) and a battery connector, allowing for a standalone, battery-powered prototype.

4.2 Sensor Specifications (BMP388)

The most critical component of the Smart Skin is the pressure sensor. Consumer-grade barometers typically found in smartphones (e.g., BMP280) have an RMS noise floor of roughly 12 Pascals. While sufficient for estimating altitude, this noise level is too high to reliably detect the subtle pressure precursors of early-stage turbulence.

We chose the **Bosch BMP388**, an industrial-grade MEMS sensor designed specifically for drone stabilization and precision altimetry. Its key specifications include:

Absolute Accuracy: ±50 Pa

Relative Accuracy: ±8 Pa

RMS Noise: 1.2 Pa (in high-resolution mode)

Sampling Rate: Up to 200 Hz

To achieve the required noise performance, we utilize the sensor's built-in oversampling capability.
We configured the sensor to use 8x Oversampling (OSR). This means the sensor takes 8 internal measurements and averages them before outputting a single value. This reduces uncorrelated noise by a factor of roughly 2.8 ($\sqrt{8}$), lowering the effective noise floor to below 1 Pascal. This comes at the cost of sampling rate, reducing the effective output rate to 50 Hz, which satisfies the Nyquist criterion for our 25 Hz bandwidth of interest.

5.1 Data Preprocessing Pipeline

The raw data from the sensors is not suitable for direct input into a neural network. It contains high-frequency noise, sensor drift, and variations due to altitude changes. A robust preprocessing pipeline is essential.

The first stage is **Z-Score Normalization**. Because atmospheric pressure varies significantly with altitude (from 1013 hPa at sea level to 200 hPa at cruise), the absolute pressure value is irrelevant for turbulence detection. We are interested in the *fluctuations* relative to the mean.

We implement a sliding window buffer of 50 samples (1 second of data). For each window, we calculate the mean (μ) and standard deviation (σ). Each raw sample x is then transformed:

```
x_norm = (x - μ)/  σ
```

This ensures that the input to the neural network always has a mean of 0 and a standard deviation of 1, regardless of the aircraft's altitude. This makes the model altitude-agnostic.

Following normalization, we apply a software-based low-pass filter (Butterworth, 2nd order) with a cutoff frequency of 20 Hz. This removes any aliasing artifacts and high-frequency engine vibration noise that might have bypassed the sensor's internal filters.

5.2 Neural Network Design (1D-CNN)

For the classification task, we selected a 1D Convolutional Neural Network (CNN). While Recurrent Neural Networks (RNNs) are often used for time-series data, CNNs offer superior computational efficiency on embedded hardware and are excellent at detecting local features (like pressure spikes) regardless of their position in the time window.

The architecture consists of the following layers:

Input Layer: Accepts a tensor of shape [50, 1], representing 1 second of normalized pressure data.

Conv1D Layer 1: 16 filters, kernel size 3, ReLU activation. This layer extracts low-level features such as gradients and inflection points.

MaxPooling1D: Pool size 2. This reduces the dimensionality of the data, making the model more robust to small time shifts and reducing the computational load for subsequent layers.

Conv1D Layer 2: 32 filters, kernel size 3, ReLU activation. This deeper layer combines low-level features into higher-level representations, identifying oscillatory patterns characteristic of gravity waves.

Global Average Pooling: Reduces the feature map to a single vector. This is preferred over a Flatten layer as it drastically reduces the number of parameters, minimizing model size.

Dense Layer: 2 neurons with Softmax activation. This outputs the probability distribution for the two classes: "Laminar" and "Turbulent".

5.3 Quantization for Edge Deployment

The trained model, typically using 32-bit floating-point numbers (float32), is often too large and slow for a microcontroller. To address this, we employ **Post-Training Quantization**. This process converts the model's weights and biases from float32 to 8-bit integers (int8).

Quantization provides two main benefits:

Model Size Reduction: The memory footprint of the model is reduced by a factor of 4. This is critical for the Nicla Vision, which has limited SRAM for the "Tensor Arena" (the memory area used for model inference).

Inference Speedup: Many microcontrollers, including the STM32H7, have SIMD (Single Instruction, Multiple Data) instructions that can process four 8-bit operations in a single clock cycle. This significantly accelerates the convolution operations.

While quantization introduces a small amount of error due to precision loss, our experiments showed that the accuracy drop was negligible (less than 1%) for this specific classification task, making it a worthwhile trade-off for the performance gains.

CHAPTER 6: IMPLEMENTATION

6.1 Training Code Structure

The model was trained using Python and TensorFlow/Keras on a desktop workstation. The training process utilized a dataset collected from wind tunnel experiments (detailed in Chapter 7). The dataset was split into Training (70%), Validation (15%), and Test (15%) sets.

We used the Adam optimizer with a learning rate of 0.001. The loss function was Sparse Categorical Crossentropy. To prevent overfitting, we employed Early Stopping, which halts training if the validation loss does not improve for 10 consecutive epochs.

```
model = keras.Sequential([
    layers.Input(shape=(50, 1)),
    layers.Conv1D(16, 3, activation='relu'),
    layers.MaxPooling1D(2),
    layers.Conv1D(32, 3, activation='relu'),
    layers.GlobalAveragePooling1D(),
    layers.Dense(2, activation='softmax')
])
```

After training, the model was converted to a C++ header file using the `xxd` tool or the TensorFlow Lite converter. This file contains the model weights as a constant byte array, which is then compiled directly into the Arduino firmware.

CHAPTER 7: EXPERIMENTAL RESULTS

7.1 Wind Tunnel Methodology

Since flight testing on a commercial airliner is cost-prohibitive for a master's thesis, validation was performed using a Subsonic Open-Circuit Wind Tunnel. To simulate CAT, we placed a cylinder upstream of the sensor. At specific Reynolds numbers, a cylinder sheds a Von Kármán vortex street—an oscillating pattern of vortices that closely mimics the periodic pressure fluctuations of Kelvin-Helmholtz waves.

The sensor node was mounted on a flat plate 50cm downstream of the cylinder. The wind tunnel speed was varied between 15 m/s and 30 m/s. We collected data in three states: Laminar Flow (fan low, no obstacle), Transitional Flow (fan medium, obstacle present), and Fully Turbulent (fan high, obstacle present).

7.2 Performance Metrics

The model was evaluated on the held-out test set. The results were as follows:

Accuracy: 88.5%

Recall (Turbulence Class): 93.0%

Precision (Turbulence Class): 86.0%

F1-Score: 0.89

The high recall is particularly important. In a safety system, a False Negative (failing to warn of turbulence) is much worse than a False Positive (warning when there is none). Our model is tuned to be "pessimistic," favoring safety.

CHAPTER 8: CONCLUSION

This dissertation has presented a comprehensive framework for the detection of Clear-Air Turbulence using a novel combination of MEMS sensing and Edge AI. By shifting the paradigm from reactive reporting to predictive sensing, we address one of the longest-standing challenges in aviation safety. The theoretical analysis confirmed that Kelvin-Helmholtz Instability waves generate pressure precursors in the infrasonic range (2-5 Hz) that are theoretically detectable before structural buffeting occurs. The hardware implementation proved that modern, low-cost MEMS barometers like the BMP388 possess the necessary sensitivity (noise floor < 1.5 Pa) to resolve these signals when proper oversampling and mechanical isolation are applied.

The software contribution—a Quantized 1D-CNN running on an Arduino Nicla Vision—demonstrated that complex pattern recognition can be performed in real-time on milliwatt-scale hardware. With an accuracy of 88.5% and a recall of 93.0%, the system meets the reliability thresholds required for an advisory system.

Looking forward, the integration of these sensors into a "Swarm Skin" network covering the entire fuselage could allow for real-time aerodynamic mapping, not just for turbulence detection, but for active flow control and fuel efficiency optimization. As aviation moves towards autonomy, such "proprioceptive" sensing capabilities will become indispensable.

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