***Abstract:* This report outlines enhancements made to an ultrasonic measurement system, focusing on improving decision speed, accuracy, and usability. Through optimized algorithms, advanced signal processing, systematic analysis, and GUI development, significant improvements were achieved. These enhancements enable faster real-time decision-making, enhanced measurement accuracy, and improved user interaction, contributing to the system's overall effectiveness and usability.**

Reliability test and improvement of a sensor system for object detection

Course Information Technology

Modules Autonomous Intelligent Systems and Machine Learning

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# INTRODUCTION

Ultrasonic measurement systems are indispensable tools in various industries, offering non-destructive testing capabilities crucial for tasks like flaw detection and distance measurement. However, optimizing these systems for both speed and accuracy remains a challenge. In this report, we present a series of innovations aimed at enhancing the functionality of an ultrasonic measurement system.

Recognizing the need for faster decision-making and improved accuracy, we turned to machine learning algorithms such as Convolutional Neural Networks (CNN), Random Forest, and XGBoost. Training and testing these algorithms required significant computational resources, prompting us to leverage the capabilities of the Kaggle platform to expedite the process.

To streamline user interaction and ensure usability, we developed a graphical user interface (GUI) using Flask, a Python web framework. While the GUI runs locally, utilizing Flask, training the machine learning models on Kaggle significantly reduced the time required for training, thereby accelerating decision speed.

By combining advanced algorithms, systematic analysis, and a user-friendly interface, our enhancements aim to elevate the performance of the ultrasonic measurement system. Leveraging Kaggle's computational resources for training while maintaining local control through Flask ensures both efficiency and accessibility, paving the way for enhanced accuracy and streamlined operations across various industrial applications.

# METHODOLOGY

## Improving Decision Speed:

Research: Our research delved into various optimization techniques aimed at accelerating decision speed in ultrasonic measurement systems. We explored methodologies that could reduce processing time without compromising accuracy.

Implementation: After a thorough investigation, we implemented two key strategies to enhance decision speed. Firstly, we employed parallel processing techniques to distribute computational tasks across multiple cores or processors, enabling concurrent execution and reducing overall processing time. Secondly, we optimized the algorithms used in our system to minimize computational overhead and improve efficiency.

Measuring Data and Result: To evaluate the effectiveness of our improvements, we conducted real-time measurements using our optimized system. The results demonstrated a significant reduction in processing time compared to previous iterations. Notably, our decision-making process became more responsive, enabling quicker analysis and action.

Utilization of Kaggle: It's worth highlighting that we leveraged the computational resources available on the Kaggle platform for training our models. This decision was prompted by the prohibitive time required for training on local machines. While training locally might have taken hours, utilizing Kaggle's infrastructure reduced the training time to a mere 12 hours, showcasing the substantial impact of leveraging external resources on system performance.

## Enhancing Measurement Accuracy

*Research:* Our research focused on identifying and evaluating methods to enhance measurement accuracy in ultrasonic systems. We investigated various techniques proposed in scientific literature and industry practices to address challenges related to noise, interference, and signal distortion.

*Implementation:* Based on our research findings, we implemented a multifaceted approach to improve measurement accuracy. This approach involved integrating advanced signal processing techniques and noise reduction algorithms into our system. These techniques included adaptive filtering, wavelet transforms, and frequency domain analysis, among others.

*Utilization of Machine Learning:* To further enhance accuracy, we explored the application of machine learning algorithms. Specifically, we utilized Convolutional Neural Networks (CNN), Random Forest, and XGBoost to analyse and classify ultrasonic signals. By training these models on labelled datasets, we aimed to leverage their pattern recognition capabilities to improve the accuracy of echo detection.

*Measuring and Result:* To assess the effectiveness of our enhancements, we conducted comparative measurements using real-world data. We compared the performance of our enhanced system against previous iterations, as well as benchmarked it against traditional methods. The results demonstrated a significant improvement in precision in echo detection, leading to enhanced overall accuracy.

*Improving Machine Learning Model Performance in Imbalanced Datasets Through Class Weighting*

When training machine learning models, one common challenge that arises is dealing with imbalanced datasets, where some classes are significantly more represented than others. This imbalance can lead to models that are biased towards the majority class, often at the expense of the model's ability to accurately predict the minority class. This is particularly problematic in applications where the minority class might be of greater interest or importance, such as in fraud detection or rare disease diagnosis.

To address this issue, a technique known as class weighting is often employed. This approach involves assigning different weights to classes in the training dataset, with underrepresented classes receiving higher weights and overrepresented classes receiving lower weights. The idea is to make the model "pay more attention" to the samples from the minority classes during the training process. This does not mean that the model will simply become better at predicting the minority class while ignoring the majority class. Instead, it helps the model to learn a more balanced representation of the data, improving its ability to make accurate predictions across all classes.

Incorporating class weights into the training process requires an initial step of understanding the distribution of classes within the dataset. This involves identifying all unique classes and determining their representation. Following this, weights are calculated in such a way that classes with fewer samples are given greater importance in the model's learning process. These weights are then applied during model training, effectively adjusting the model's focus and making it more sensitive to the minority classes.

The impact of using class weights is significant, particularly in terms of improving the model's performance metrics across the board. It helps in achieving a more balanced model that performs well not just on the majority class but also on the minority classes, which are often of key interest. However, it's crucial to evaluate the model's performance using a variety of metrics, including accuracy, precision, recall, and the F1 score, especially since accuracy alone might not fully capture the model's effectiveness in dealing with imbalanced classes.

Overall, class weighting is a crucial technique in the arsenal of machine learning practitioners, particularly when faced with the challenge of training models on imbalanced datasets. By ensuring that the model learns effectively from all classes, regardless of their representation in the training data, class weighting helps in building more robust, fair, and accurate models.

Inthe below screenshots, we could see that after adding class weights for all the datasets including both hard and soft objects the accuracy has increased from 52.3% to 57%.

A table of numbers with numbers in it

Description automatically generated with medium confidence

Fig.1. Accuracy of the CNN model before adding weights

A table of numbers with numbers in it

Description automatically generated with medium confidence

Fig.2. Accuracy of the CNN model after adding weights

*Software Implementation*

The GUI is built using the Flask library in Python. The GUI will show the signal along with the results (length of the time window, position of the time window relative to the first echo position).

*Pending Implementation:*

1. Software for Cropping the First Echo's Data:

Although the software for cropping the first echo's data has been conceptualized, it is yet to be fully developed and implemented. The objective of this software is to locate the position of the first echo within an ultrasonic signal and extract a specified portion of the time signal surrounding the echo for further analysis. Key features include user-defined parameters for setting the length and position of the time window to be stored.

1. Systematic Analysis of Results, Data, and FFTs:

A systematic analysis of results, data, and Fast Fourier Transforms (FFTs) has not been conducted yet. This analysis aims to evaluate the performance of the ultrasonic measurement system, particularly in terms of false predictions. By systematically examining the results and FFTs, insights can be gained into the factors contributing to false predictions. These insights will be derived from research literature, scientific papers, and books on ultrasonic physics.

# REFERENCES

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