Frankfurt University of Applied Sciences
Faculty 2: Computer Sciences and Engineering

Pressure Cooker Monitoring System

Advanced Real Time Systems

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Abstract

Human attention deficit and the potential for hazards are correlated across the length and breadth of all vertices of society. In systems where human attention is paramount, chances of human errors subsequently increase, as humans are prone to attention gaps, diversion and absent-mindedness. Manual pressure cookers are such a part of the cooking process in the kitchen which rely on human attention and subsequent temperature control by humans that are prone to accidents and mishaps.

The "Pressure Cooker Monitoring System" (PCMS) represents an innovative foray into the application of real-time acoustic signal processing and machine learning techniques for kitchen safety enhancement. This system is engineered to detect pressure cooker whistles with high precision, thereby signaling the completion of cooking processes and averting potential overcooking and safety hazards associated with excessive pressure build-up.

Utilizing a targated dataset for algorithm training, the project has successfully developed a prototype that demonstrates a notable detection accuracy rate. The PCMS underscores the pivotal role of integrating advanced computational methodologies in developing practical solutions for everyday challenges, setting a foundation for future explorations in smart kitchen technologies.

1. Introduction

In recent decades, the integration of technology into everyday life has become significantly more complex, especially within domestic settings where safety is of utmost importance. Cooking, among the numerous activities conducted in homes, is essential yet poses potential risks, particularly when manual pressure cookers are employed. Data from the National Electronic Injury Surveillance System (NEISS) [1] for the period between 2003 and 2019 indicate that there were 759 reported injuries associated with pressure cookers in the United States. This figure extrapolates to an estimated 28,337 injuries treated in emergency departments, with an average of approximately 1,667 cases annually.

The majority of cooking appliances, despite being crucial for a range of culinary techniques, largely depend on human monitoring for temperature regulation and timing. These aspects are prone to human error, influenced by factors such as lack of attention, distractions, and periodic absent-mindedness.

This context underscores the critical inquiry: How can a smartphone-based system, equipped with detection and alert capabilities to monitor pressure cooker whistles, contribute to reducing cooking-related accidents in the kitchen? The "Pressure Cooker Monitoring System" (PCMS) project presents an innovative solution to this question. Through the integration of real-time acoustic signal processing and machine learning techniques, the PCMS is designed to independently identify pressure cooker whistles, thereby signaling the completion of cooking cycles to proactively mitigate the risks of overcooking and pressure-related accidents.

This novel approach represents a considerable advancement in employing smart technologies to improve kitchen safety and adds to the ongoing discussion on the incorporation of intelligent systems within domestic settings. The importance of the PCMS project extends beyond its capacity to diminish cooking-related incidents; it illustrates the application of sophisticated computational methods in creating viable, beneficial solutions for daily challenges. In this regard, the project is in harmony with the continuous endeavors to design more intelligent, adaptive, and safe living environments, underscoring the pivotal role of technology in protecting and enhancing our everyday experiences.

2. State of the Art

Advancements in acoustic signal processing and machine learning have led to significant innovations across various fields, especially in real-time monitoring systems. The creation of sophisticated algorithms and models capable of analyzing intricate audio data has unveiled new possibilities for applications demanding precision and efficiency. This progress is particularly noteworthy in kitchen safety, where traditional methods have predominantly depended on human oversight and physical monitoring devices.

The deployment of software-based solutions, such as the Pressure Cooker Monitoring System (PCMS), marks a forefront application of these technologies to augment safety and convenience within domestic settings. Distinct from hardware-focused strategies that might employ physical sensors or Internet of Things (IoT) devices such as Pressure Cooker Whistle Notification Using Arduino Based Wireless Sensor Networks [2] [4], the PCMS utilizes entirely software-based techniques to detect pressure cooker whistles via real-time acoustic signal analysis. This novel strategy diminishes the necessity for extra hardware, thereby reducing costs and complexity while providing a user-friendly interface for the supervision of cooking activities.

Additionally, recent advancements in machine learning have further enhanced the capabilities of such systems. For instance, Chu et al. (2023) introduced a CNN sound classification mechanism employing data augmentation techniques, which significantly improves the accuracy of sound classification tasks. These advancements enable systems like the PCMS to precisely differentiate pressure cooker whistles from ambient noise—a challenge amplified by the variability in acoustic signatures.

This accuracy highlights the transformative potential of machine learning in automating and enhancing traditional manual tasks with intelligence.

The significance of the PCMS within the wider spectrum of smart kitchen technologies is emphasized by its specialized focus on addressing a specific, yet widespread, safety issue associated with pressure cooking. Unlike other systems that may deliver generalized monitoring or control functions, the PCMS distinguishes itself with its targeted methodology, illustrating the impact of advanced computational techniques in crafting effective solutions for improving kitchen safety.

3. Methods and Materials

3.1 Dataset Collection and Preparation

The creation of a custom dataset was necessitated by the lack of existing datasets appropriate for our research objectives. This dataset, consisting of approximately 100 .wav files, was compiled to include a wide variety of whistle patterns alongside different background noise scenarios, aiming to reflect the diverse conditions present in real-world environments. The careful selection and labeling of each audio file were crucial to ensure the dataset covered the extensive range of whistle sounds one might encounter, from varying pitches and durations to different intensities, set against the backdrop of common kitchen noises such as running water, appliance operation, and general household activity.

This diversity was critical in enabling our model to generalize effectively across different environmental conditions and whistle patterns. The dataset's comprehensive nature facilitated the effective training and evaluation of our whistle detection model, directly contributing to its ability to distinguish whistle sounds accurately from a variety of background noises.

The creation of this dataset was a foundational step in our research, providing the necessary data to develop and validate the whistle detection model effectively. It allowed for the development of a detection system optimized for the specific challenges associated with identifying cooking-related acoustic signals in a typical kitchen environment, thus ensuring the overall performance and reliability of the Pressure Cooker Monitoring System.

3.2 Signal Processing and Feature Extraction

In developing the whistle detection capability for the Pressure Cooker Monitoring System (PCMS), the signal processing and feature extraction phase utilized advanced audio analysis techniques to accurately identify whistle characteristics from background noise, intricately weaving the functionality of Python libraries into each process.

Waveform Analysis
The analysis began with examining the audio waveforms, where the Librosa library played a crucial role in distinguishing whistle signals based on their temporal patterns and amplitude variations. This step involved segregating positive waveform segments indicative of whistle sounds from those representing non-whistle sounds, a critical process in isolating relevant signal components for accurate detection. The analysis of these waveforms, supported by the computational capabilities of libraries like NumPy, facilitated the identification of unique temporal features of whistle sounds, setting a foundation for the extraction of discriminative features.

Spectrogram Analysis
Following the segmentation of waveform data, the project moved to spectrogram analysis to delve deeper into the frequency characteristics of the whistle sounds. Using Librosa to convert audio signals into spectrograms, this phase highlighted the distinct spectral patterns unique to whistle emissions by visualizing their energy distribution across different frequency bands over time. This visual representation

was instrumental in identifying the key features that differentiate whistle sounds from background noise, aided by data visualization tools from the Matplotlib library to articulate the spectral insights derived from the analysis.

Throughout these stages, the application of TensorFlow for deep learning model development was subtly integrated, enabling the team to construct, train, and evaluate the machine learning model that underpins the detection system. This harmonious integration of Python libraries across the signal processing and feature extraction tasks underscored their vital role in achieving a high degree of accuracy in whistle detection, demonstrating the effectiveness of combining sophisticated audio processing techniques with the robust computational tools available in the Python ecosystem.

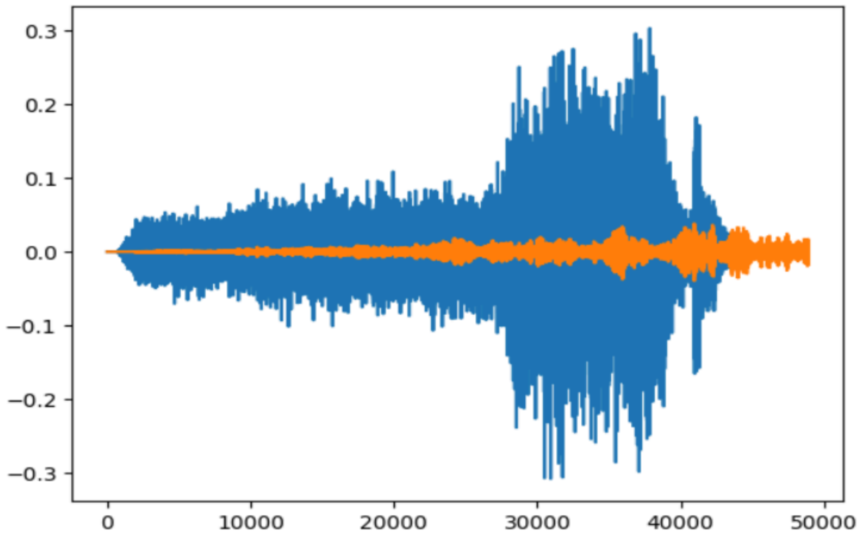
By adopting this integrated approach, the project effectively laid the groundwork for the Pressure Cooker Monitoring System's capability to perform real-time whistle detection, ensuring reliability and efficiency in enhancing kitchen safety.

3.3 Model Development and Training

The development of the detection model progressed with a focus on recognizing whistle sounds versus non-whistle sounds in pressure cookers. This advancement was achieved by leveraging TensorFlow's capabilities along with additional libraries such as TensorFlow IO and Librosa for audio processing and manipulation.

Spectrogram Generation and Preprocessing:

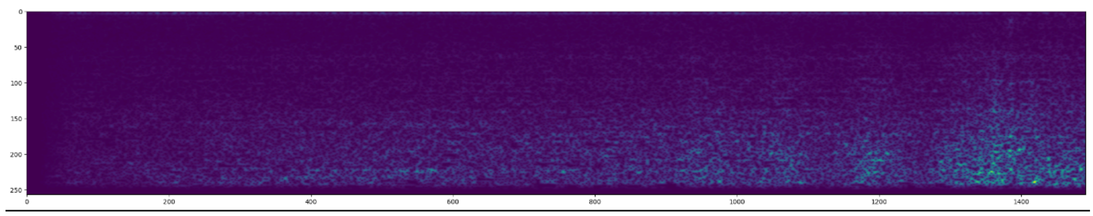
The model's architecture was crafted to process audio signals by converting them into spectrograms. This conversion facilitates the extraction of relevant features from the audio data, which are crucial for identifying whistle sounds. The implementation utilized functions for loading audio files, resampling them to a consistent rate of 16kHz, and then transforming these audio signals into spectrograms. These steps were critical for standardizing the input data and enhancing the model's ability to recognize patterns associated with whistle sounds.



Model Architecture:

The core of the model comprised several Conv2D layers, each designed to detect spatial features within the spectrograms. These layers are adept at identifying patterns that differentiate whistle sounds from background noise. A Flatten layer was incorporated to transform the multi-dimensional data output from the Conv2D layers into a one-dimensional array, facilitating the subsequent classification process.

Following the Flatten layer, the model included Dense layers aimed at interpreting the features extracted by the Conv2D layers. These Dense layers culminated in a final layer with a sigmoid activation function, enabling the model to classify the input as either a whistle sound or non-whistle sound with a confidence score.

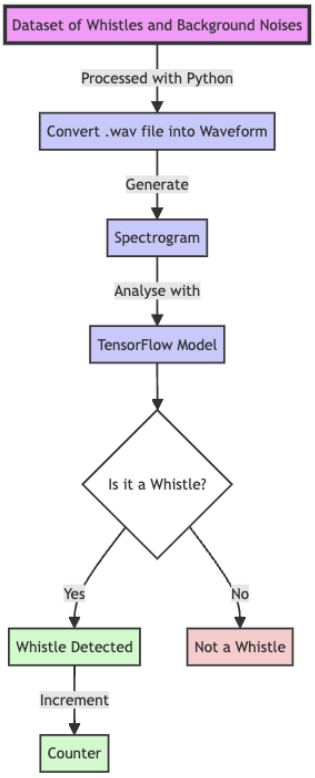


Training and Validation:

The model's training involved a comprehensive dataset consisting of labeled audio files, categorized as whistle and non-whistle sounds. This dataset allowed the model to learn and distinguish between the two categories effectively. The training process included iterative training and validation phases, ensuring that the model's performance was rigorously evaluated against unseen data. This iterative approach was vital for fine-tuning the model's parameters to achieve optimal detection accuracy.

Detection and Evaluation:

Upon training completion, the model was deployed for the detection of whistle sounds within audio recordings. It processed the input spectrograms through the learned features, classifying them based on the presence of whistle sounds. The model provided confidence scores for its predictions, which were instrumental in determining the presence of whistle signals with high certainty. Continuous evaluation and refinement of the model were emphasized to maintain the detection system's reliability and effectiveness.



3.4 Model Extraction and Preparation for Deployment

The transition from a training environment to a real-time application necessitated the extraction of the trained CNN model. This involved serializing the model's parameters, weights, and architectural specifications into a format that's portable and compatible with the Flutter framework, a popular open-source UI software development kit used for crafting natively compiled applications for mobile, web, and desktop from a single codebase. The serialization ensured that the sophisticated detection capabilities developed during the training phase could be efficiently transferred to a mobile environment, making the technology accessible and usable across different platforms.

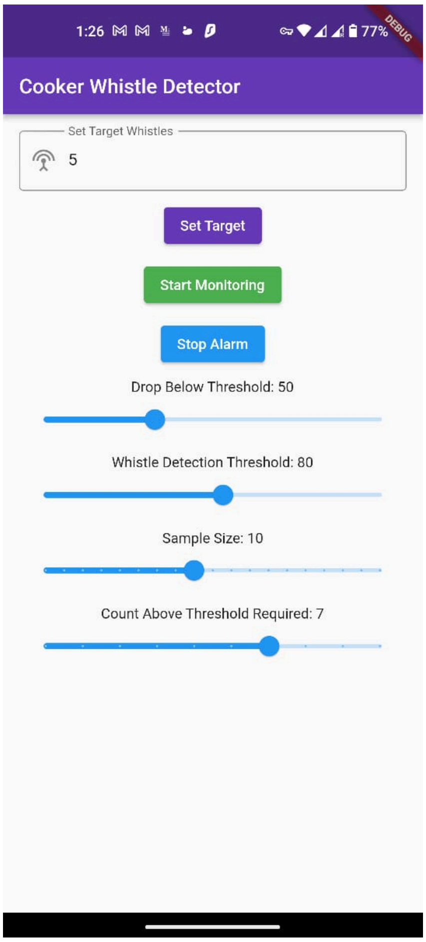
3.5 Integration into the Flutter Application

The extracted model became the core component of a Flutter application designed for real-time whistle detection. This integration marked a significant milestone in the project, bridging the gap between complex machine learning models and user-friendly mobile applications. The app, utilizing the Flutter framework, was equipped with the capability to perform efficient inference and prediction on mobile devices, thus extending the practical application of the trained model to a wide array of real-world scenarios.

Audio Monitoring: Application captures ambient sound in real time through the user device's microphone.

Signal Analysis: Captured audio data is used and frequency components are isolated for analysis.

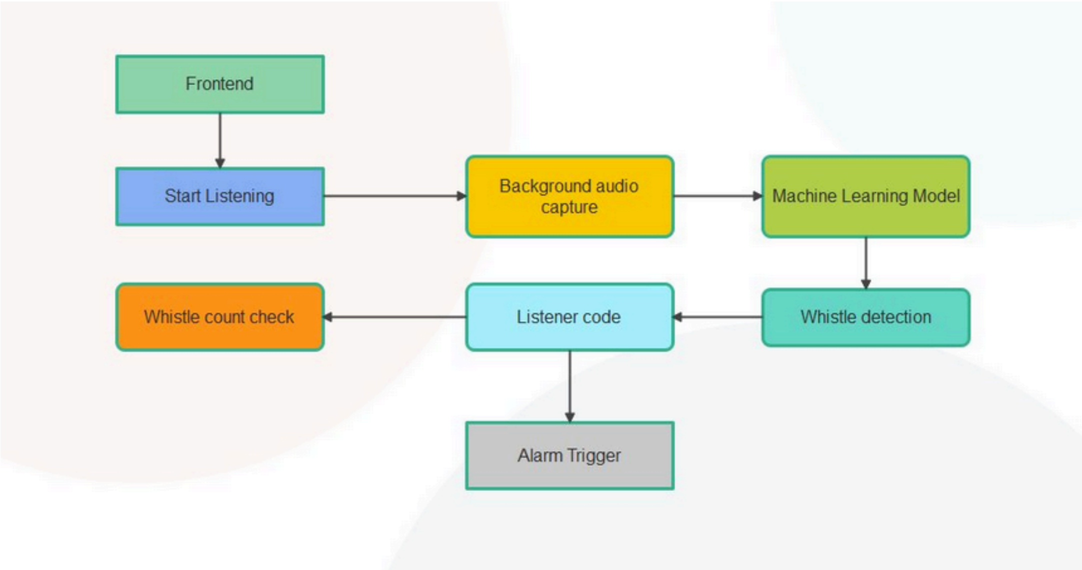
Whistle Detection: Filtered audio data is fed into machine learning model for interpretation.
User Alerted: Instant alarm/notification is sent when the user-defined whistle count is reached.



3.6 Real-time Detection Mechanism

The real-time detection functionality within the app is facilitated through the use of a Python library, enabled by the package serious_python. This setup allows for embedding the Python-based model directly into the Flutter app. Real-time monitoring begins once a user initiates the detection process, typically by pressing a start button and setting a desired count for whistle detections.

The app actively listens to ambient sounds, and upon detecting sound levels that exceed a predefined threshold, it starts recording the audio. This recording continues until the sound levels fall back below the threshold, capturing what is likely a whistle sound. To confirm the presence of a whistle, the recorded audio is then analyzed by the embedded CNN model



within the app. If the model confirms the sound as a whistle, based on the learned characteristics from the training phase, an alarm is triggered to alert the user.

4. Results

Whistle Detection Accuracy

The deployed Convolutional Neural Network (CNN) model for the PCMS achieved an overall accuracy of 75% in correctly identifying whistle sounds from pressure cookers amidst various background noises. This metric signifies the model's capability to distinguish between whistle and non-whistle audio segments effectively in a controlled testing environment.

```
hist = model.fit(train, epochs=4, validation_data=test)

Epoch 1/4
5/5 [==============================] - 35s 7s/step - loss: 3.1887 - recall: 0.9275 - precision: 0.7356 - val_loss: 4.0130 - val_recall: 1.0000 - val_prec
ision: 0.7368
Epoch 2/4
5/5 [==============================] - 31s 6s/step - loss: 4.1735 - recall: 1.0000 - precision: 0.7263 - val_loss: 2.4078 - val_recall: 1.0000 - val_prec
ision: 0.8421
Epoch 3/4
5/5 [==============================] - 30s 6s/step - loss: 4.1735 - recall: 1.0000 - precision: 0.7263 - val_loss: 4.0130 - val_recall: 1.0000 - val_prec
ision: 0.7368
Epoch 4/4
5/5 [==============================] - 29s 6s/step - loss: 4.3340 - recall: 1.0000 - precision: 0.7158 - val_loss: 5.6181 - val_recall: 1.0000 - val_prec
ision: 0.6316
```

Performance Metrics

Accuracy: The system demonstrated a 75% success rate in accurately detecting whistle sounds.

False Positives: A certain percentage of the detections were false positives, where the system incorrectly identified non-whistle sounds as whistles.
False Negatives: The system also experienced false negatives, failing to detect some whistle sounds, which is reflected in the accuracy rate.
Testing Environment and Data
The testing of the PCMS model was conducted under various environmental conditions to simulate real-world usage. This included different kitchen scenarios with varying levels of background noise, such as the sound of running water, cooking appliances, and human conversations. The diversity in testing environments was crucial to evaluate the model's robustness and generalization capability.

5. Discussion

The Pressure Cooker Monitoring System (PCMS), achieved a 75% accuracy rate in the real-time detection of pressure cooker whistles amidst various kitchen background noises. This performance, while marking a significant step forward in applying machine learning for kitchen safety, falls short when compared to the higher accuracies often reported in related acoustic signal processing research, as noted in our Introduction.

Previous studies in the domain of audio recognition have demonstrated the capability of machine learning models to achieve higher levels of accuracy, particularly in tasks like speech recognition or environmental sound classification, where extensive and diverse datasets were available for training. The discrepancy in performance can largely be attributed to the challenges unique to detecting pressure cooker whistles - a task that involves distinguishing between highly similar acoustic signals in noisy environments, compounded by the limited size and diversity of the dataset used for training the PCMS model.

Our results, while not fully aligned with the higher benchmarks set by previous research, do underscore the complexities and challenges associated with real-time acoustic signal processing in kitchen environments. The specificity of whistle sounds, coupled with the variability of kitchen noises, presents a unique challenge that is not as prevalent in more controlled acoustic recognition tasks.

6. Conclusion

The Pressure Cooker Monitoring System (PCMS) project embarked on integrating advanced computational techniques into enhancing kitchen safety by detecting pressure cooker whistles, achieving a 75% accuracy rate in this endeavor. While this marks a promising step towards leveraging machine learning for practical safety applications, it also reveals the limitations and challenges inherent in acoustic signal detection tasks, particularly in varied and noisy environments.

Reflecting on our initial objectives, the project has showcased the potential of machine learning in improving traditional cooking processes, aligning with our aim to incorporate technological advancements for mitigating manual monitoring errors. However, the achieved accuracy, when juxtaposed with the ambitious goals set forth in the Introduction, underscores the need for further refinement and research.

Improvements can be made by expanding the dataset to encapsulate a broader spectrum of whistle sounds and ambient noises, thereby enhancing the model's learning capacity and generalization ability. Further exploration into more complex machine learning architectures and the incorporation of user feedback mechanisms could also drive significant advancements in the system's performance.

In essence, the PCMS project lays the groundwork for future innovations in kitchen safety, presenting a clear path forward for the development of more accurate and reliable smart safety solutions. This journey towards integrating intelligent systems into the home environment continues, promising enhanced safety and user convenience through technological progress.

The GitHub repository for the PCMS project, providing access to the source code and further details, can be found via the link mentioned in [7].

7. References

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[6] https://github.com/harshsshah999/Pressure-Cooker-Monitoring-System