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Machine Fault Detection with Sound Patterns using Deep Learning

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Abstract: This study attempts to give the user the machine's operational condition while simultaneously detecting flaws or damage in big industrial machinery in real-time. However, due to the complexity of real-world systems and the clear presence of nonlinear elements, it is highly challenging to diagnose a machine malfunction using standard approaches based on mathematical models. A computer-aided diagnostic system with artificial intelligence (CADS-AI), which aids in early fault diagnosis, can resolve this issue. To assure that the CADS solution can be trusted, a machine failure detection system based on sound patterns is created in this study. The YAMNet Model classified the sounds as normal or abnormal with an accuracy of 78.31%. By using window inference on the audio file with a mean score, the predicted output was decoded. By using real-time audio input or uploading machine sounds to the system, the proposed solution can be inferred.

***Index Terms* - Pattern Recognition, MachineLearning, Machine Fault Diagnosis, Audio Processing, Acoustic emission signals.**

I. INTRODUCTION

Numerous industrial processes in the manufacturing sector demand a level of quality and speed that humans are unable to meet. Fans, pumps, sliders, and valves are just a few of the pieces that make up an industrial machine, which is frequently utilized in factories. A knowledgeable technician can recognize the sound of a malfunctioning machine part and halt production right away so that broken machine parts may be fixed. Mechanical equipment condition monitoring and diagnosis are essential tools for ensuring the equipment's dependable and safe functioning. Methods for diagnosing faults can be broadly categorized as signal- based, model-based, active/hybrid, and knowledge-based. To detect the signal patterns for the system failure diagnostics using data-driven methodologies, a sizable amount of historical data is necessary. Signals like as current, temperature, electrical tension, and vibrations are frequently analyzed using predictive maintenance and data-driven techniques. To diagnose faults, signal-based characteristics are extracted. To prevent redundant information and also to considerably reduce the feature dimensions, the retrieved features must be subjected to feature selection algorithms. The chosen features are then applied to various statistical and machine-learning models for fault diagnostics.

This paper suggests a deep learning-based system for real-time machine defect detection that may be implemented on mobile or web platforms. To ensure confidence in computer-aided machine defect prediction, the optimum deep learning architecture for inference is chosen based on training accuracy and data with suggested validation. The suggested resolution is displayed below,

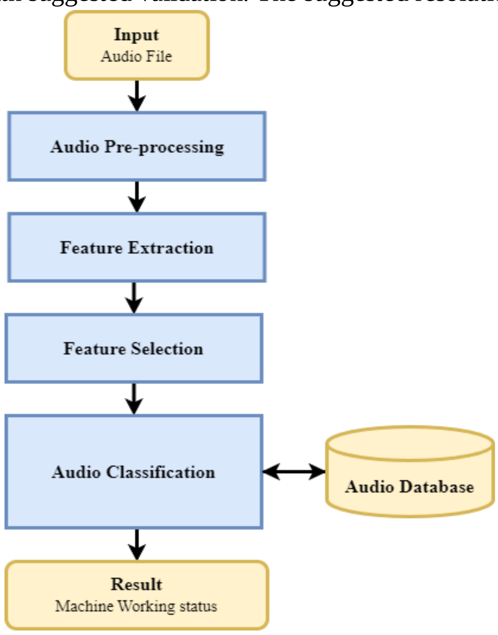

Fig 1 : Working of Proposed solution

Mechanical equipment condition monitoring and diagnosis are essential tools for ensuring the equipment's dependable and safe functioning. Only by mastering the equipment's health status in good time can technicians successfully locate and fix hidden problems, increasing production efficiency and lowering business losses. Signal-based, model-based, active/hybrid, and knowledge-based methods can all be used to diagnose faults.The knowledge-based techniques, also known as data-driven techniques, need a significant amount of historical data to identify the signal patterns for the system problem diagnostics.

Predictive maintenance and data-driven procedures are widely used to evaluate signals like the current, temperature, electrical tension, and vibrations that are captured by the use of sensors. The signal-based features are retrieved for fault diagnostics. The retrieved features must be submitted to feature selection methods to minimize redundant information and drastically reduce the feature dimensions. The chosen characteristics are then used for defect diagnosis utilizing a range of methods based on conventional statistics and machine learning models. Signal processing techniques have been widely examined to ascertain the correlations between vibration data or acoustic emissions and REB health state.

II. LITERATURE SURVEY

To extract all of the features and identify the operating status of the machine using classification algorithms, numerous signal processing approaches have been researched in the frequency domain, time domain, and time-frequency domain recently. It is preferred to evaluate and extract the features from non-stationary signals using time-frequency domain techniques.

In a study by Hayashi, they used variations in the power spectrum to find defects in an electromagnetic valve. They created a feature vector with a length of 240 units by using frequency bands between 55 and 1250 Hz with a 5 Hz spacing. An ANN with 30 hidden neurons classified the faults. The network was trained using both regular valve operation sounds and noises produced by valves with 2 mm holes or 5 mm cracks. Although they did not provide numerical findings, they concluded that the system is workable for fault identification. Maniak used sound analysis to check the quality of the sound signaling devices being produced. The coefficients were utilized as an input for an ANN with 50 hidden neurons that were trained on 160 non-faulty samples and 40 samples with errors.

Shengqiang employed a multi-domain feature vector in this study to identify problems in axial piston pumps using vibration and sound signals. Centrobaric and mean square frequencies are among the chosen frequency domain features, along with pulse factor, kurtosis, and time domain features. They use kernel-level principles. accuracy of 68% from sound signals and 72% from vibration signals are obtained when a component analysis is used in decision-making.

By Salazar-Villaneuva, induction motor fault detection was investigated. They acquired the frequency spectrum of the signals and five intrinsic mode functions as characteristics. They evaluated the chosen features' efficiency in fault detection and concluded that they would work well for fault detection.

Additionally, Shutao used intrinsic mode functions in a study case where they looked at transformer fault detection. On getting Hilbert spectra, they apply the Hilbert- Huang transformation to the IMFs. According to the study case, the method can be used to find defects in transformers.

III. MATERIALS AND METHODS

A. DATASET

We are using the MIMII dataset, which is a dependable dataset for analyzing and examining malfunctioning industrial machines. Fans, pumps, valves, and sliders are just a few of the four basic types of industrial machinery that make noise. Regular noises last for between 5000 and 10000 seconds for each model, whereas anomalous sounds last for about 1000 seconds. Numerous anomalous sounds, including contamination, leakage, rotating unbalance, and rail damage, were captured to simulate a real-world event. Additionally, the machine sounds were combined with background noise that was captured in numerous actual factories.

An eight-channel microphone array with a sampling rate of 16 kHz and a bit depth of 16 was used to record the sounds.

We have used 1000 audio samples from MIMII Dataset and the data distribution is given in the below table,

Table 1 : Data distribution

Audio samples distribution			
Audio Type	**Total audio samples**	**Train**	**Test**
Fan - Normal	100	70	30
Fan - Abnormal	100	70	30
Pump - Normal	100	70	30
Pump - Abnormal	100	70	30
Slider - Normal	100	70	30
Slider - Abnormal	100	70	30
Valve - Normal	100	70	30
Valve - Abnormal	100	70	30

B. METHODOLOGY

1) DATA COLLECTION AND PRE PROCESSING

In this step, the pre-recorded noises in wav file are used by the system. These sounds are only used when developing a system because changes need to be tested against the reference set. The device can also simply be modified to capture real-time sound with a computer-connected microphone. The first step in preprocessing audio is to convert it to a mono signal. We do not employ information that can be received from other channels, and the mono conversion makes the feature extraction procedure easier. All reference sounds that are used are considered to have been recorded in stereo with microphones set near enough to one another to prevent noticeable latency between channels. In the next stage, we resample the data to a sampling rate of 16 kHz to efficiently acquire the frequency spectrum. To remove random noise that could negatively impact system performance, particularly the false detection rate, we used light noise reduction. The features are extracted from each window separately because the system is designed to analyze the signal constantly without the requirement for overlapping signals.

2) FEATURE EXTRACTION

Feature extraction is a process of audio signal processing, a branch of signal processing, which deals with the modification or processing of audio signals. Through the conversion of digital and analog signals, it reduces undesired noise and balances the time-frequency ranges. The audio data is transformed into spectrograms using a feature extractor integrated into the YAMNET Model and then sent to the MobileNet. Unstructured audio representations like spectrograms and MFCCs are taken into account by the deep learning method. The patterns are automatically extracted, and feature extraction is automatic. The availability of data and computing power also support it.

2.1 Spectral Bandwidth

The spectral bandwidth or spectral spread is derived from the spectral centroid. It is the variance from the spectral centroid or the spectral range of interest surrounding the centroid. It is directly related to how timbre is perceived. The energy dispersed between frequency bands and the bandwidth is directly inversely related.

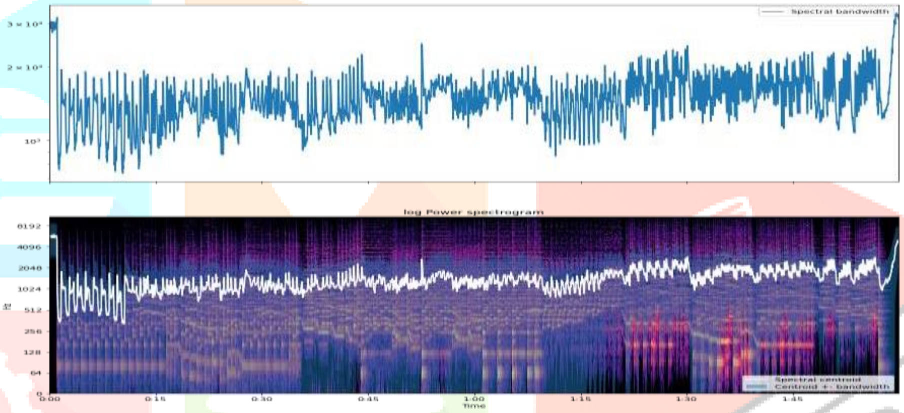

Fig 2 : Representation of Spectral bandwidth and LogPower spectrogram

2.2 Spectrogram

A spectrogram is a visual depiction of the spectrum of frequencies of an audio signal as it varies with time. Hence it includes both time and frequency aspects of the signal. It is obtained by applying the Short-Time Fourier Transform (STFT) on the signal. In the simplest of terms, the STFT of a signal is calculated by applying the Fast Fourier Transform (FFT) locally on small time segments of the signal.

3. FEATURE SELECTION

Recursive Feature Elimination (RFE), a method that ranks features according to some metric of their relevance, is what we utilized. This feature selection method operates by repeatedly removing the least useful characteristic. Each iteration evaluates the significance of each trait, and the less significant ones are deleted. For some measures, the relative relevance of each feature can change when assessed over a different subset of characteristics during the stepwise feature elimination procedure, necessitating the requirement for the recursion. It involves fitting a machine learning model with the initial set of features and calculating the classification performance.

4. MACHINE SOUND CLASSIFICATION

We have trained YAMNet to distinguish between normal and pathological machine sounds. The 521 audio event classes are predicted by a pre-trained CNN that was created for SED tasks and uses the Mobilenet V1 Depthwise-separable Convolution Architecture. This effective framework was created to integrate low-latency AI models into mobile apps where computing resources are severely constrained. A depth-wise separable convolution is used in MobileNet designs in place of the conventional convolution.

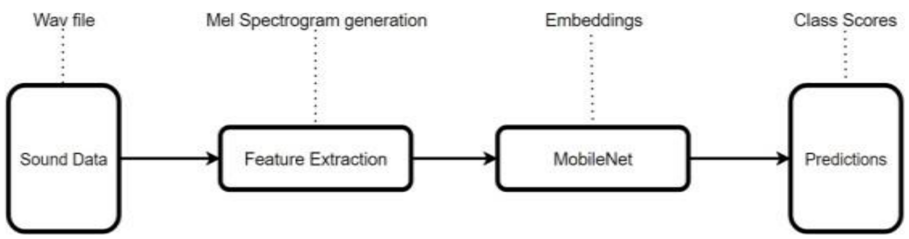

Fig 3 : Working of YAMNet model

A Mel spectrogram feature map is used. The feature maps are built using coefficients obtained from sound representations of time and frequency. The human perception of sound, however, is not linear in terms of frequency content. It is well established that at lower frequency ranges, humans hear pitch more precisely.

5. FAULT DETECTION IN MACHINES

Our method's final step is real-time machine failure detection, which informs the user of the machine's operational state. The method's foundation is the ability to hear changes in the sound and spot potentially problematic areas. This strategy offers benefits. First, we require sets of the machine's recognized noises produced under various operation settings.

A complete set of sounds is hard to find and takes a lot of time to collect. As a result, it is simpler to adapt the system to new usage situations. Second, we can use a classification technique that is less complicated and doesn't call for any prior learning. We use a reference vector as a benchmark during the initial stage of fault identification. Reference vectors with averaged values across many windows are supported by the system. We use the Euclidian distance to calculate the difference between the reference vector and the target feature vector. A threshold value decides whether to suspect a signal is flawed. Each application's threshold value is changed separately. Second, a higher threshold value is used to identify situations where a problem is likely to occur. The model stores the suspected fault segments in a database for additional analysis to get precise fault circumstances. After that, the suspicious sounds are manually labeled to indicate the various fault conditions. The reference feature vector, the target feature vector, their difference, and the window position in a sound file are all included in the saved data. To acquire a set of sounds for typical operation, the system additionally saves periodic sounds without any indication of a malfunction.

IV. RESULTS AND DISCUSSION

The implemented model predicts the fault in machines as "normal" and "abnormal" along with the part name ofthe industrial machines by converting the input audio file into waveform format. Various anomalous sounds, including contamination, leakage, rotating unbalance, and rail damage, are captured in the input file's WAV format. The machine noises were combined with background noise that was captured in numerous actual factories. An eight-channel microphone array with a sampling rate of 16 kHz and a bit depth of 16 was used to record the sounds. The feature extraction of audio properties like Spectral Bandwidth and Spectrogram from the input audio file is an important step in audio signal processing, a subfield of signal processing. It has to do with altering or processing audio signals. It reduces unwanted noise and balances the time-frequency ranges by converting digital and analog signals. The input audio file will split into 10 parts to perform windows inference which helps to provide the specifications of the audio in each window frame of the audio file. It also gives thesound level which helps determine the abnormal working of a machine part. The model will display the status of the machine after the fault diagnosis.

The results obtained are given below,

1) Fan Normal

i) Input – Normal Fan Audio

ii) **Audio pre-processing**

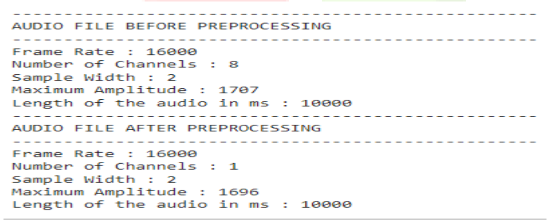

Fig 4 : Audio pre-processing of Normal Fan audio

iii) Feature Extraction

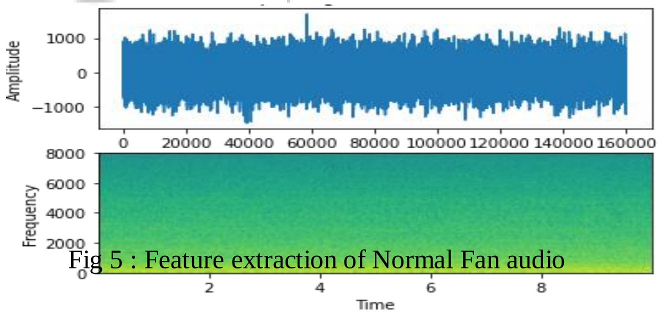

Fig 5 : Feature extraction of Normal Fan audio

iii) Audio Windows inference and Sound Level

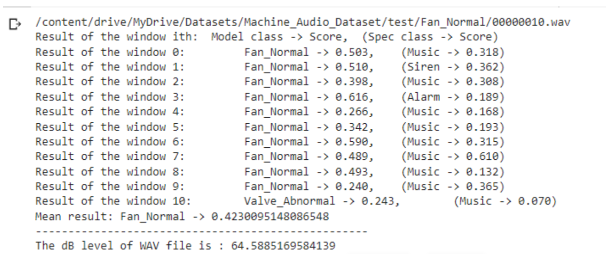

Fig 6 : Windows inference for Normal Fan audio

iv) Machine working status display

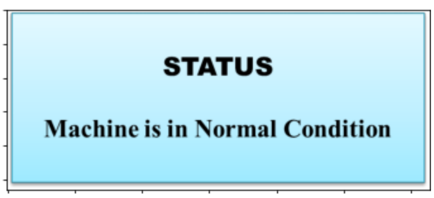

Fig 7 : Machine fault alert display for Normal fan

2) Pump Abnormal

i) Input – Pump Abnormal Audio

ii) Audio pre-processing

```
--------------------------------------------------
AUDIO FILE BEFORE PREPROCESSING
--------------------------------------------------
Frame Rate : 16000
Number of Channels : 8
Sample Width : 2
Maximum Amplitude : 4160
Length of the audio in ms : 10000
--------------------------------------------------
AUDIO FILE AFTER PREPROCESSING
--------------------------------------------------
Frame Rate : 16000
Number of Channels : 1
Sample Width : 2
Maximum Amplitude : 3128
Length of the audio in ms : 10000
```

Fig 8 : Audio pre-processing of Pump Abnormal audio

iii) Feature Extraction

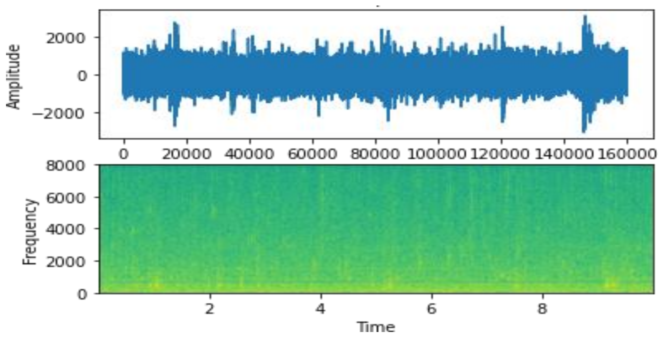

Fig 9 : Feature extraction of Pump Abnormal audio

iv) Audio Windows inference and Sound Level

```
/content/drive/MyDrive/Datasets/Machine_Audio_Dataset/test/Pump_Abnormal/00000021.wav
Result of the window ith:  Model class -> Score,  (Spec class -> Score)
Result of the window 0:        Pump_Abnormal -> 0.910,        (Thunderstorm -> 0.769)
Result of the window 1:        Pump_Abnormal -> 0.347,        (Rustle -> 0.286)
Result of the window 2:        Fan_Abnormal -> 0.251,  (Rustle -> 0.173)
Result of the window 3:        Pump_Normal -> 0.512,   (Pour -> 0.600)
Result of the window 4:        Pump_Abnormal -> 0.483,        (Water -> 0.341)
Result of the window 5:        Pump_Abnormal -> 0.743,        (Boat, Water vehicle -> 0.170)
Result of the window 6:        Pump_Abnormal -> 0.840,        (Rain -> 0.905)
Result of the window 7:        Pump_Abnormal -> 0.544,        (Boiling -> 0.175)
Result of the window 8:        Pump_Abnormal -> 0.426,        (Speech -> 0.193)
Result of the window 9:        Pump_Abnormal -> 0.297,        (Inside, small room -> 0.114)
Result of the window 10:       Pump_Abnormal -> 0.168,        (Vehicle -> 0.096)
Mean result: Pump_Abnormal -> 0.48089858889579773
--------------------------------------------------
The dB level of WAV file is : 69.34031636876871
```

Fig 10 : Windows inference for Pump Abnormal audio

v) Machine working status display

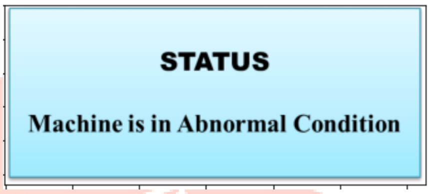

Fig 11 : Machine fault alert display for Pump Abnormal

3) Confusion Matrix of the Fault Detection Model

It is a performance measurement for a machine learning classification problem where the output can be two or more classes. It is a table with 10 different combinations of predicted and actual values. This fault detection model based on sound patterns has achieved 78.31% accuracy.

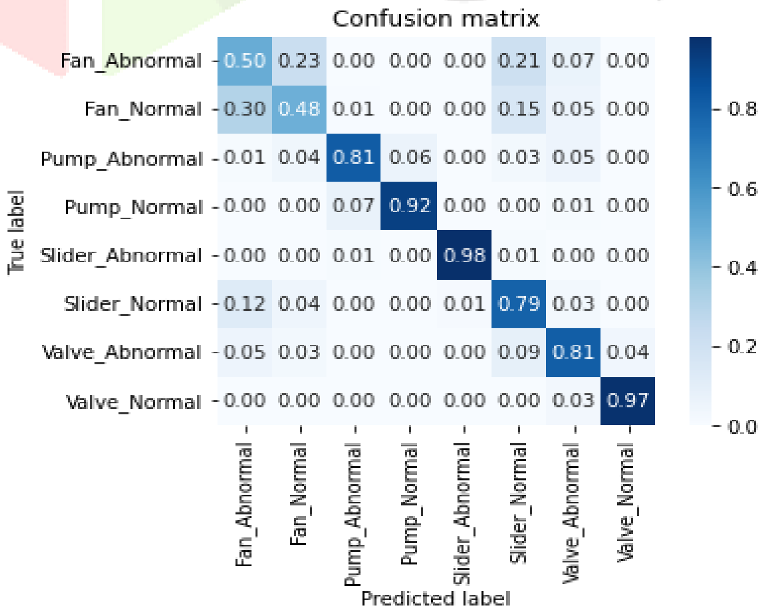

Fig 12 : Confusion Matrix for Machine Fault detection model

We propose a novel approach to detect faults in real time in industrial machines and classify normal and abnormal sounds from machine parts in heavy industrial machines by using a Computer Aided Diagnosis (CAD) solution using the sound patterns emitted by the machines along with the sound level and give machine working status to the user. This system helps in the early diagnosis of faults in machine parts which may lead to the failure of the entire machine in a non-invasive way by giving the sound level which can be used to identify the severity of the damage by the user. It uses image representations of sound features extracted from Spectral Bandwidth and Spectrogram based on deep learning. Additionally, before feeding the extraction features to the machine learning classifiers, we use NCA to minimize the number of features. High precision in spectral bandwidth and spectrogram images is achieved by our suggested methods. The results are encouraging in terms of applicability for early defect machine detection and industry noise levels

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