Identifying the volume of a vessel using audio generated from exterior percussive strikes and Machine Learning

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Problem Statement

Identifying volumes within enclosed vessels are essential to many processes in the industrial field and is often done with various level indicators and transmitters, with visual gauges, or with other methods of measuring. However, it becomes more difficult to identify those volumes if those options are not available. This paper explores a solution of identifying the volume of a vessel by using audio generated from exterior percussive strikes and Machine Learning.

Literature Review

"Monitor concrete moisture level using percussion and machine learning,"
- by Liqiong Zheng, Hao Cheng, Linsheng Huo, Gangbing Song. -

This explores the use of machine learning to solve a dilemma of accessing large structures that have high exposure to moisture and determining the structural integrity in a more reliable and unique method. This relates to volume identification as this project also seeks to add another safe and reliable method to the current repertoire of identifying volume within a vessel.

" Automatic Classification of Drum Sounds: A Comparison of Feature Selection Methods and Classification Techniques"
- by Perfecto Herrera, Alexandre Yeterian, Fabien Gouyon

- Comparison of various classification techniques to differentiate between a multitude of musical percussion sounds.

Experimental Setup and Collection of Data

The setup involved several pieces of equipment:

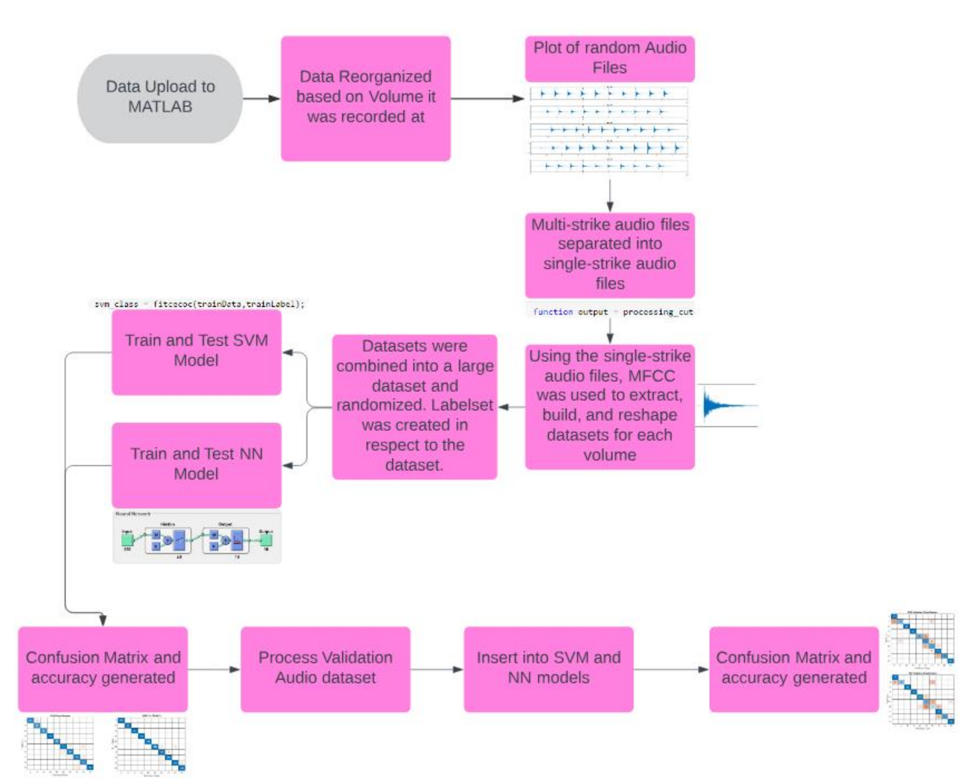
- Wooden Pedestal
- Stainless Steel Hammer
- An aluminum pot of approximately 62.61 gallons
- An android phone with audio recording capabilities

The pot was measured to calculate 10 different volume quantities to translate to an internal gauge. Water was added to meet each of the 10 calculated thresholds and at each threshold, the lid was placed on it, and the hammer was used to strike an identical location on the pot 10 times to create a single audio file. 340 audio files, each with 10 strikes, was collected for general training and testing data. An additional 20 audio files, each containing 10 strikes was collected independently for validation testing. Audio files were collected evenly across the 10 calculated thresholds and were labeled as such.

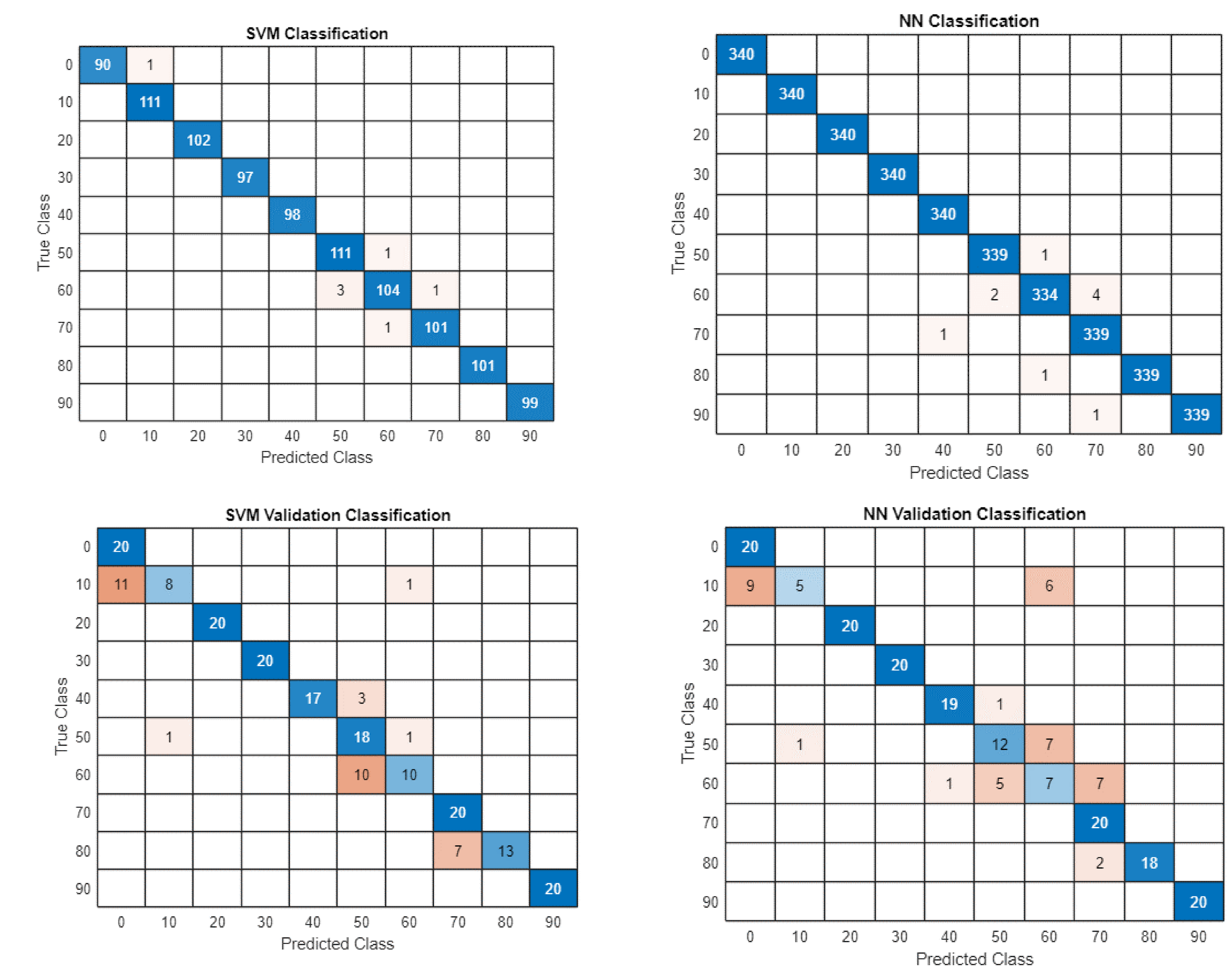
The data was labeled according to the volume threshold it was recorded at. The first digit corresponded to the percentage the pot was filled and the number after the underscore indicated the iteration of the audio file recorded.

Method

- Once the data was collected, the audio files were imported into **MATLAB** and was divided into separate datasets based on naming convention of the files.
- When the data was organized by volume at which it was created, a random plot of audio from each volume category was generated for examination.
- Every audio file was processed further to separate out the 10 strikes in each audio file to be 10 separate audio datasets. This was done with a local function, labeled as processing_cut. This local function identified the 10 strikes within each audio file and made an audio cut to separate the 10 strikes. This was done by identifying the 10 peaks from each strike, starting the audio cut a preset distance before the peak and a preset distance after the peak.
- MFCC was used to extract features and reshape the dataset to prepare for the next steps. The different volume datasets were assembled into a larger single dataset and the labels were combined into the same order.
- Both the audio dataset and labels were randomly re-ordered the same way and split into a training and testing dataset using a 70/30 ratio.
- A Support Vector Machine (SVM) model was trained and tested with this dataset to generate a model and general accuracy.
- A Neural Network (NN) model was trained and tested with the same dataset to generate a model and general accuracy.
- Once complete, a validation audio dataset was processed in the same manner as the starting dataset, randomized, and directly inserted into the models generated for SVM and NN. A validation accuracy was calculated to determine the effectiveness of the trained models.
- A confusion matrix was generated for both the initialized models and both the validation results for each model.



Results, Analysis and Discussion



Initial Test Set
SVM Classification Accuracy: 99.31%

NN Classification Accuracy: 99.71%

Validation Test Set
SVM Classification Accuracy: 83.00%

NN Classification Accuracy: 80.50%

- Initial results when a total of 1200 audio strikes were collected had similar accuracy on the initial test, but when checking the validation test set, the accuracy plummeted to be less than 15%. After examining the code for errors, and re-examining SVM and NN processing within MATLAB it was determined that it was not a coding issue.
- Data collected was increased to 3600 audio strikes and that resulted in a significant increase in the validation test set to be greater than 80% as seen above.
- There seems to be a correlation between the amount of data collected and the performance of each model of machine learning.
- The SVM model with this dataset was more accurate when tested against the validation dataset however the both SVM and NN were equally accurate in the initial testing.
- Some issues in identifying volumes at 20% and around 60-70% full. This could be related to quality of the validation dataset.

Conclusion

- With a reduced size of dataset, the performance of machine learning models was reduced drastically, by increasing the dataset size, the performance was enhanced significantly.
- With this size dataset, SVM seems to give a slightly more accurate interpretation however within MATLAB, there is more control over the parameters of the NN model.
- For future testing of this theory, more data needs to be collected to further improve the machine learning models' accuracy and more testing with various parameters needs to be conducted on the NN model to confirm if a particular model out-performs the other or not.
- This theory then needs to be tested on larger vessels to deem if it is plausible for industrial purposes and needs to be tested against various liquid materials to determine if SG can affect the results.

Acknowledgements

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References

1. Dr. Song's knowledge of Machine Learning and his course material
2. Lucidchart.com to produce a flow-chart