# CHATTER PREDICTION USING IMAGE PROCESSING

*Project Report Submitted in Fulfilment*

*of the Requirements for ME623*

*by*

*Lolugu Nityasri (210103068)*

*Guglavath Tharun (210103050)*

*Gundeti Srivardhan (210103130)*

**DEPARTMENT OF MECHANICAL ENGINEERING**

**INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI**

**GUWAHATI – 781039, ASSAM**

## Acknowledgements

We would like to express our sincere gratitude to our course instructor Dr. Rinku Kumar Mittal for his unwavering support and guidance throughout the course project. We would also like to thank Abhishek Punia (TA, Research Scholar) for helping us out in acquiring the dataset.

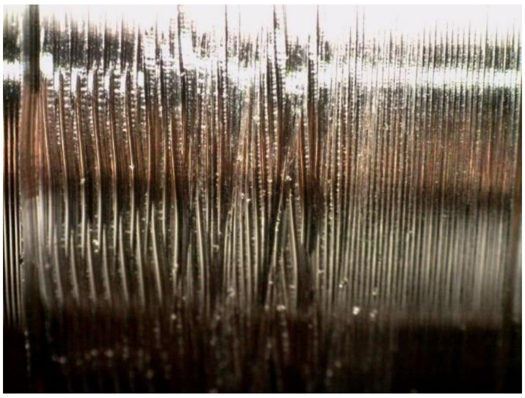
## Introduction

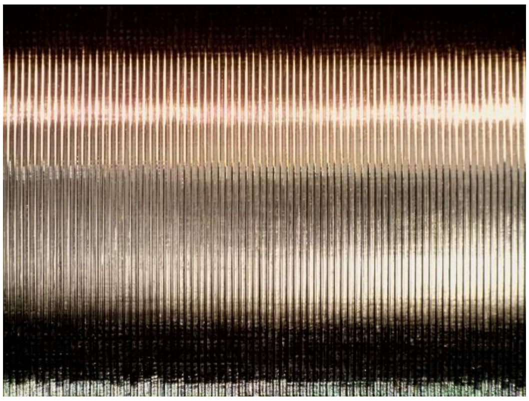
In the realm of mechanical cutting and machining, the phenomenon of self-excited vibration, commonly referred to as 'Chatter,' presents a significant challenge, adversely impacting both the quality of the final product and the longevity of the cutting tools. The primary objective of our study is to leverage machine learning techniques to discern whether a given image of a machined surface exhibits signs of chatter or remains chatter-free. Our analysis focuses exclusively on surface images of the workpiece obtained through turning operations, with data collected across various depths of cut and spindle speeds. Chatter in turning manifests as undesired vibrations occurring in the turning tool, lathe, or the workpiece itself during machining processes. It triggers with detrimental consequences including unsatisfactory surface quality, diminished tool lifespan, and potential tool failure.

## Methodology

*Data Collection* → *Data Cleaning* → *Analyse Data* → *Data Model Building* → *Interpreting Results*

Select your materials thoughtfully and refrain from combining disparate materials while machining. Execute turning operations carefully, pausing the machine at different depths of cut and spindle speeds to photograph the machined surface. Confirm the sharpness of your cutting tool and optimize the machining environment. Employ a tripod stand for your camera to mitigate vibrations and utilize a high-resolution lens for precise image capture. Consistently maintain a sizable dataset for dependable outcomes, ensuring images are captured without disruptions to preserve accuracy.





Chatter                                  Chatter-free

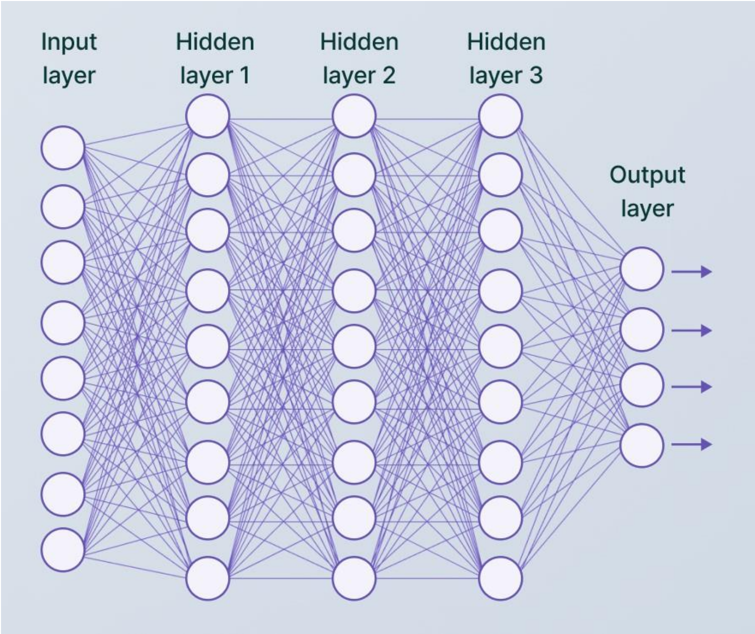
Be mindful of capturing chatter-free images, as surface irregularities can pose challenges during neural network training and model building After capturing the images, prepare a CSV file containing the data extracted from these images using libraries used PIL, frameworks used are NumPy, OS, CSV. Extract image properties and convert it into grayscale image.

## Classification Method

Convolutional neural networks (CNNs) are a popular type of neural network for image classification tasks. Compared to traditional neural networks, CNNs can integrate spatial information of input data, resulting in better image processing performance. The basic building block of a CNN is the convolutional layer, which applies a learned set of filters to the input data, producing a set of activation maps corresponding to different input features.

These activation maps are then fed into a pooling layer, which reduces the dimensionality of the data by selecting the maximum or average value in a small window of the activation map. The output of the pooling layer is then fed into a fully connected layer, producing the final classification output. The fully connected layer is similar to the output layer in traditional neural networks, except that it retrieves its input from the outcome of the convolutional and pooling layers instead of directly from the input data.

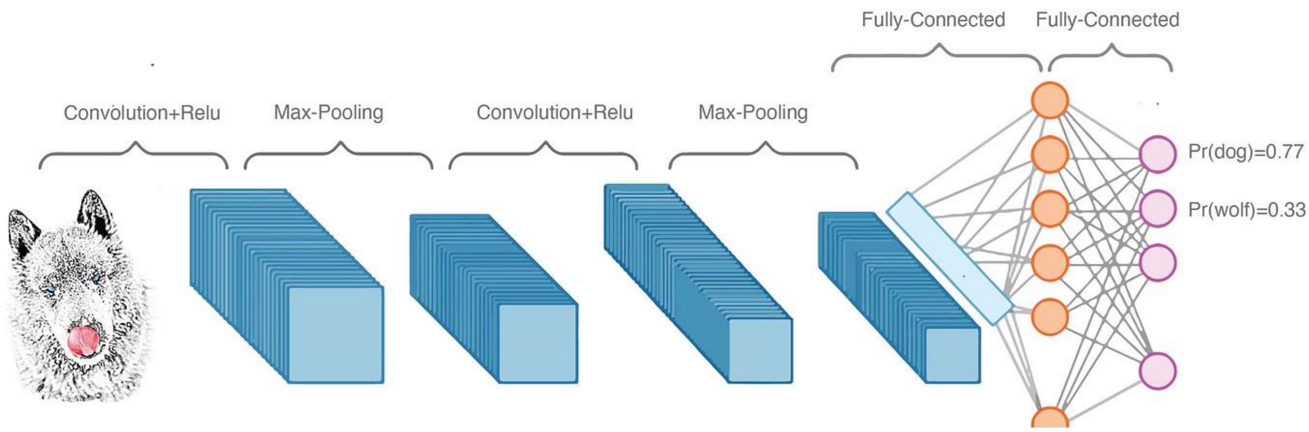
One advantage of CNNs is their ability to learn features directly from data instead of relying on handcrafted features. This result is achieved through backpropagation, adjusting the learned parameters of the convolutional filters during training to maximize the classification accuracy of the output. Here we used machine learning/Deep learning methods to identify and classify images to detect vibration processes.




Convolutional Neural Network

Sequential model consists of a series of layers stacked sequentially. Each layer in the sequential model passes its output to the next layer in the sequence. The architecture of this sequential model comprises several layers, including convolutional, pooling, and fully connected layers.

The convolutional layers have a fixed filter size of 3 × 3 and a stride of 1. There are typically multiple convolutional layers such as dense each followed by a Rectified Linear Unit (ReLU) activation function (64 ) and sigmoid 1. max-pooling layers are applied. These max-pooling layers have a fixed pool size of 2 × 2. Max-pooling helps in down sampling the feature maps and reducing their dimensionality**.** Convulation 2D has 32 filters each 3×3**.** Input shape has dimesonas (640,480,1)



Here we focus on adjusting the hyperparameters of the model, with particular attention given to the batch size, optimizer, loss function, and normalization operation. After processing, the image files are divided into several parts and again divided into training, and testing sets at a ratio of 0.74,0.26.

The Ratio of correctly predicted instances to the total number of instances in the dataset.

$$\boldsymbol{Accuracy = \frac{TP + FF}{TP + FF + TN + FP}}$$

Recall refers to the ability of the model to correctly identify all relevant instances of a class in the input data. It measures the proportion of true positives (correctly identified instances) out of all actual positive instances. Higher recall indicates that the model is effectively capturing the relevant features associated with the class.

$$\boldsymbol{Recall = \frac{TP}{TP + FN}}$$

Precision measures the proportion of true positive predictions (correctly predicted instances) out of all positive predictions made by the model. It focuses on the accuracy of the positive predictions made by the model. Higher precision indicates fewer false positives, meaning the model is making fewer incorrect positive predictions.

$$\boldsymbol{Precision = \frac{TN}{TP + FP}}$$

A high recall value (closer to 1) indicates that the CNN effectively identifies most of the actual positive cases. It misses very few relevant examples. A low recall value (closer to 0) suggests the CNN is missing a significant portion of the positive cases. It might be prone to false negatives.

# Results and Discussion

To analyse our model in better way we use confusion matrix. The confusion matrix appears as shown in the figure below.

In the below matrix, the two columns represent the predicted values. Similarly, both the rows represent the actual values. Typically, the matrix consists of four categories: True Positive (T.P.), which means that the prediction and the real value are both positive; True Negative (T.N.), meaning that the forecast and the actual value are both negative; False Positive (F.P.), meaning the prediction is positive while the real value is negative; False Negative (F.N.), meaning the forecast is negative while the actual value is positive.

Of the 24 test data samples, there are 12 chatter samples and 12 chatter-free samples. However, the prediction model provided 10 chatter samples and 2 chatter-free samples; therefore, there were two cases in which model made a wrong prediction. From the 12 images of the stable machining group,7 was assigned to the chatter group, and the remaining 5 images were correctly classified.

**Predicted Values**

| Actual values | | Chatter (1) | Chatter-free (0) |
|---|---|---|---|
| | Chatter (1) | 10 | 2 |
| | Chatter-free(0) | 7 | 5 |

**By evaluation metrics :**

- The obtained accuracy is : 0.62
- The obtained precision is : 0.71
- The obtained Recall is : 0.42
- The obtained F1-score is : 0.53

# Conclusion

We utilized sequential CNN modelling to classify a dataset comprising 91 pairs of visual surface part data achieving 100% train accuracy and 62% test accuracy. By increasing the epochs, the model gets trained in a better way. Due to the limited size of our dataset (91 samples), our model achieved a modest accuracy of around 62%. However, we expect a significant improvement in accuracy (above 80%) by expanding the dataset with more samples and enhancing the micro visual profile of the images. We intend to utilize our model for real-time chatter prediction in machining. This involves employing high-FPS cameras to capture live machining processes and analyzing the images in real-time using Conv3D. Concurrently, we will continue training the model in real-time to enhance its predictive capabilities. Model's applications span CNC, micro-turning, and various manufacturing processes, promising significant improvements in efficiency and quality.

# References

[1]Andreas Otto, Melih C. Yesilli, Firas A. Khasawneh : "Chatter detection in turning using machine learning and similarity measures of time series via dynamic time warping" , Journal of Manufacturing Processes, Volume 77, May 2022, Pages 190-206

[2] Andres Bustillo, Ibone Oleaga, Carlos Pardo, Juan J. Zulaika : "A machine-learning based solution for chatter prediction in heavy-duty milling machine" , Measurement, Volume 128, November 2018, Pages 34-44

[3] Guillem Quintana , Joaquim Ciurana : "Chatter in machining processes: A review" , International Journal of Machine Tools and Manufacture, Volume 51, Issue 5, May 2011, Pages 363-376

[4] Quang Ngoc The Ho, Thanh Trung Do, Pham Son Minh, Van-Thuc Nguyen and Van Thanh Tien Nguyen : "Turning Chatter Detection Using a Multi-input Convolutional Neural Network via image and Sound Signal" , Machines, Volume 11.

[5] Othman O. Khalifa, Amirasyid Densibali, Waleed Faris : "Image processing for chatter identification in machining processes"