Quantitative Performance Analysis from Discrete Perspective: A Case Study of Chip Detection in Turning Process

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Abstract: Good performance of the Machine Learning (ML) model is an important requirement associated with ML-integrated manufacturing. An increase in performance improvement methods such as hyperparameter tuning, data size increment, feature extraction, and architecture change leads to random attempts while improving performance. This can result in unnecessary consumption of time and performance improvement solely depending on luck. In the proposed study, a quantitative performance analysis on the case study of chip detection is performed from six perspectives: hyperparameter change, feature extraction method, data size increment, and concatenated Artificial Neural Network (ANN) architecture. The focus of the analysis is to create a consolidated knowledge of factors affecting ML model performance in turning process quality prediction. Metal peels such as chips are designed at the time of metal cutting (turning process) and the shape of these chips indicates the quality of the turning process. The result of the proposed study shows that following a fixed recipe does not always improve performance. In the case of performance improvement, data quality plays the main role. Additionally, the choice of an ML algorithm and hyperparameter tuning plays an essential role in performance.

1 INTRODUCTION

The concept of ”zero human intervention” stepped into the scene with the rise of Artificial intelligence (AI). AI is the science of intelligent machine development (Watson, 2005) (McCarthy, 2007). Machine Learning(ML) is a black-box AI technology which learns an unknown function based on provided data (Zhang, 2020). Sensor technologies have advanced in an unprecedented manner. These new sensors can produce large amounts of data which paves the way for ML applications in the manufacturing domain (Kusiak, 2018), (Tiwari, 2021) . Distributed and autonomous manufacturing has laid a new milestone (Wang, 2015), (Zhuang, 2007). Data in the manufacturing domain are stored for a short period for maintenance purposes and have a chaotic structure (Wuest, 2016).

These data can foster automation in the manufacturing domain with the application of ML for managing uncertainties (Zhang, 2020), tool condition monitoring (Alfaro-Cortes, 2020), process modelling, adaptive control (Monostori, 2003), quality prediction (CHO, 2020) etc. Cloud and IoT-based devices are used for deploying models for scheduling (Jian, 2021), self-organised task scheduling (Chen, 2018), and manufacturing collaboration (Tao, 2019). Supervised and unsupervised learning are the two main contributors to manufacturing from an ML perspective (Dogan, 2021) (Bricher, 2020). The widely used algorithms are the Support vector machine (SVM) (Liao, 2019), Artificial Neural Network (ANN) (Casalino, 2016), Decision Trees (DT) (Ronowicz, 2015), and k Nearest Neighbors (kNN) (Kong, 2016).

In the period 2015-2020, research publications were mainly focused on the application of ML in the manufacturing domain (Sheuly, 2021), (Hamidur, 2023). However, after 2020 only an application of ML to a certain domain is no more considered a significant contribution to the state of the art (Doulgkeroglou, 2020), (Syafrudin, 2018), (Romero, 2019).

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Additionally, according to (Chui, 2017), 64% of total work spent in the manufacturing domain can be automated with the latest technology instead of human resource and it could save 478 billion working hours. ML with significant performance can reduce economic loss and required time in manufacturing (Zhao, 2020), (Uzkent, 2019), (Brisk, 2019). As a result of this new requirement for improved performance, the application of ML with changed ML architecture, versatile data source, and edge device found its way into the manufacturing domain. However, good performance is a prerequisite in the case of ML applications in the manufacturing domain (Sharmin 2021). No research study quantifies the change in performance with perspective variation such as a change in ML architecture, the inclusion of versatile data sources, and hyperparameter tuning. This can give rise to a random search for performance improvement methods which is a time-consuming and unrealistic method.

In the proposed study, a case study combining cutting-edge technologies such as ML, embedded systems and cloud technology of chip detection is presented where a change in performance is quantified with perspective variation such as hyperparameter change, the inclusion of feature extractor and new data source, change in ML model architecture.

The proposed study contributes to the state-of-the-art works by creating hyperparameter-tuned models, followed by performance comparison from a different perspective and a complete hardware setup. The proposed work will create an efficient path of performance improvement for the future researcher.

Most turning process prediction systems predict surface roughness (Singh, 2007), cutting parameters (Jurkovic, 2018), and tool life (Laghari, 2019). To our knowledge, no other study implements a turning process prediction system for machine health monitoring with ML, embedded systems and cloud technology followed by an analysis of different perspectives. A local manufacturing company [1] manufactures cutting tools that cut metal into a predefined shape. One of the cutting processes is turning (kim, 2018). In the turning process, the workpiece moves, and the cutting tool remains stationary while cutting the metal. The by-product of the turning process is metal chips and technicians examine these chips to understand whether the turning process is in a good condition. Figure 1 shows the turning process using a cutting tool and Figure 2 shows chip classes:(a)acceptable chip (b)optimal chip (c)bad chip.

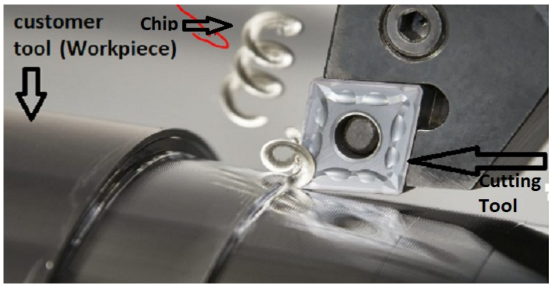


Figure 1: Turning Process with a cutting tool.

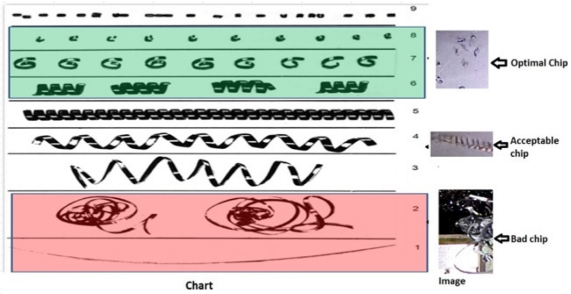


Figure 2: Chip classes depending on size.

In this proposed study, the final ML model runs on Raspberry Pi replacing the human technician by predicting the chip class based on the chip image and machine parameters. In addition, the images were saved on the Azure cloud platform. The rest of the paper is structured as follows: Section 2 presents an overview of the approach, section 3 presents the implementation method, section 4 shows the results and finally section 5 concludes the study with a discussion.

2 OVERVIEWS OF APPROACH

This research study started with the offline process by gathering domain knowledge, data, requirements, and ideas provided by the local manufacturing company (Figure 3). The formulated problem was to automate the turning process using ML models and quantification of change in performance because of the changed perspective. The state of the art in the manufacturing domain was reviewed to find concurrent ML algorithms appropriate for the formulated problem. ML algorithms such as ANN, Convolutional Neural Network (CNN), SVM, kNN and RF were selected. There are two types of data: the image of chips and numerical machine parameters.

[1] https://www.secotools.com/

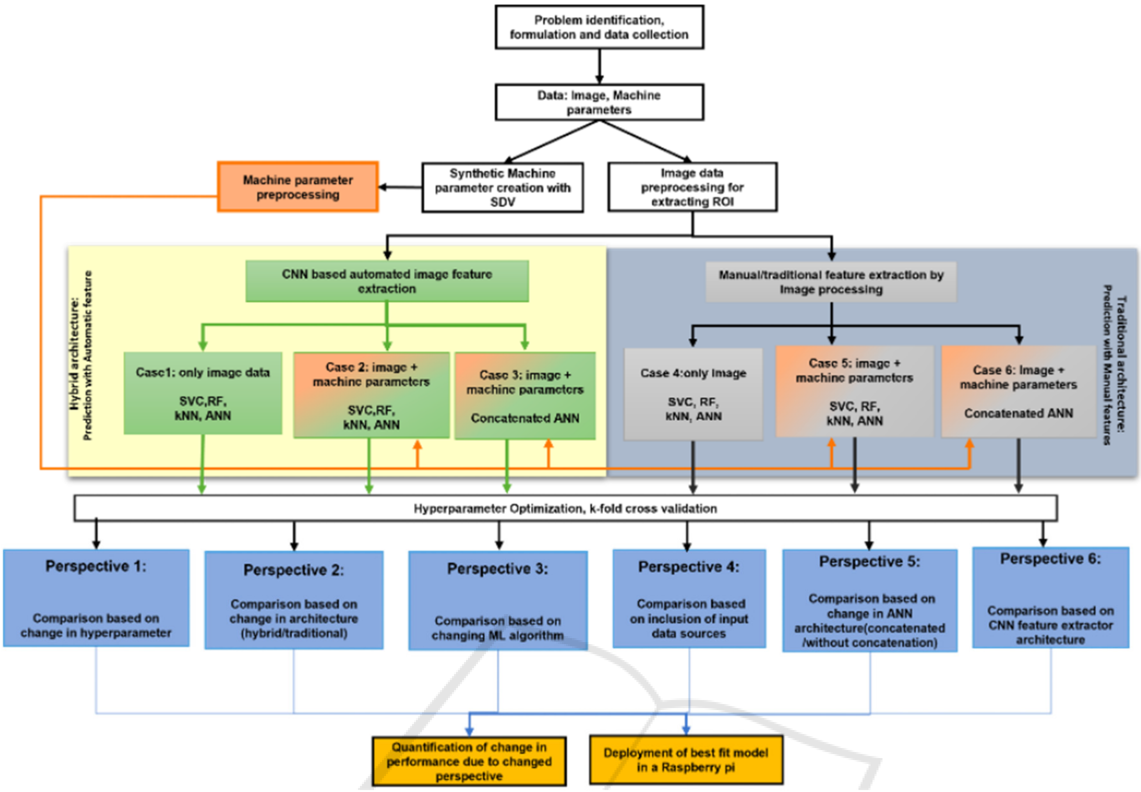


Figure 3: Step-by-step offline process.

On image data several pre-processing steps such as Gaussian blur filter, foreground mask, and Canny edge filter were performed to convert the images to an appropriate form. For the numeric machine parameters cardinality, missing values were checked. After pre-processing, classification models were trained on the processed data. Two sets of models were created: one set with automatic features such as features extracted with help of CNN which are named ‘hybrid architecture’. Conversely, another set of models was created with manually extracted features which are named ‘traditional architecture’.

Both hybrid and traditional architecture have varying inputs. Certain models were created with only image data as input such as Case 1 and Case 4 (coloured in green) while certain models were created with both image and machine parameters as input such as Case 2, Case 3, Case 5, Case 6 (coloured in green and orange). Two types of models were created for ANN: one set with concatenated architecture (Case 3 and Case 6) and the other set without concatenation (Case 2 and Case 5). In the case of concatenated architecture, two ANN models, one considering machine parameters as input (Model 1) and one considering the image as input (Model 2) were concatenated at the final layer. Conversely, in the case of a model without concatenation machine parameters were combined with the image and the combined data was used as input to the ANN model.

All the models were created with hyperparameter optimization. SVC, RF, and kNN were created with 5-fold cross-validation while ANN (both concatenated and without concatenation) were created with train, validation, and test split (80%, 10% and 10%). In the following stage, the created eighteen ML models were evaluated to quantify the change in performance with change in perspective. The considered perspectives are

1) Change in hyperparameter.
2) Change in architecture (Hybrid/traditional feature extraction).
3) Change in ML algorithm (ANN, SVC, RF or kNN).
4) Inclusion of new data sources such as machine parameters.
5) Change in ANN architecture (Concatenated or without concatenation).
6) Change in CNN feature extractor architecture (shallow layer or deep layer).

The ML model with the best performance was deployed in raspberry pi. In case of bad chips, the raspberry Pi switched the red LED on and signalling the technician.

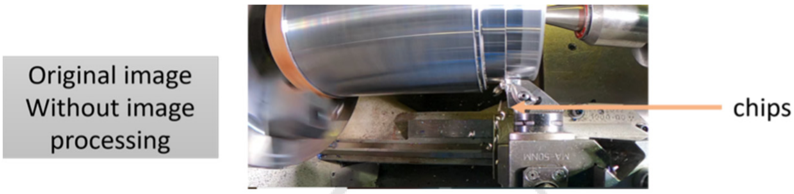
3 IMPLEMENTATIONS

3.1 Data Collection and Pre-Processing

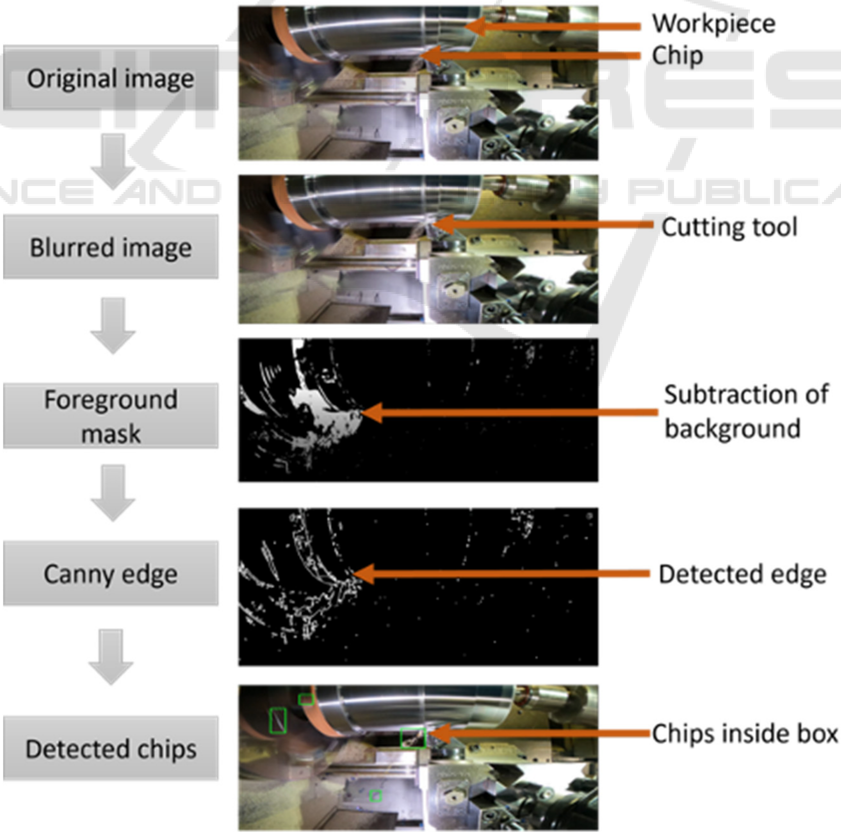
There was no image-capturing system at the local manufacturing company. To capture images during the turning process a GoPro Hero 9 camera was installed on top of the workpiece. An additional light source was used in the setup. In total, 42 videos were captured with the highest speed, feed, and chip breaker (a tool that breaks the chips). A total of 20023 images were extracted from the videos for training. In addition, 6429 images were extracted for testing.

In the case of machine parameters, 2105 data instances were provided by the manufacturing company. Synthetic Data Vault (SDV) (Watson, 2005) is a set of libraries that were used to generate synthetic data of the same format and statistical properties. The SDV was used to create a hierarchical statistical model of the machine parameters. This fitted model was subsequently used to generate additional data instances. A total of 20023 data instances of machine parameters were created to align with 20023 image data.

The primary goal of pre-processing is to improve image quality by suppressing irrelevant information and enhancing important features for ML classification. However, this step adds additional time to the classification. Figure 4b shows pre-processing



a) Undetected chips because of an absence of image processing



b) Detected chips because of image processing

Figure 4: Comparison of the image in the presence and absence of image processing techniques.

steps performed on the images while Figure 4a shows an image without pre-processing. It is visible that without pre-processing chip detection is not possible. In this work, the images were at first smoothed with help of a Gaussian filter (Figure 4b). Gaussian filter reduces the details of an image by replacing pixel values with a value closer to the nearby pixel value. This smoothing helps detect edges. In the later stage, a foreground mask was applied to the blurred image. The white area in the figure represents the moving objects (rotating workpieces and chips) and the black area is the stationary background. The stationary background is removed from the image to enhance only the moving chips. To detect the edges of an object, the canny edge detection technique is used. In the proposed work, canny edge detection is used to separate chips from other moving parts. Changes in pixel, intensity are used to define the boundary. A fast change in pixel intensity is regarded as an edge. In the last stage, the green bounding box is showing the potential chips. In the case of numerical data, the missing values were first located and populated with the median value. In the later stage, the cardinality of the variables was checked, one of the variables had cardinality 1 (all the values were the same), and it was removed from the dataset because it does not contribute any information. To identify outliers minimum and maximum values of each variable were investigated. Outliers are absent in the dataset. The variables were scaled to the range [0,1] resulting in similar effects from all data instances.

3.2 Feature Extraction with CNN

CNN was used for feature extraction. Two CNN models were trained on the image data and the final layer output of CNN is used as the input feature. The first model has seven layers while the second model was created with two layers. The performance of these two models was compared considering accuracy.

3.3 Classification Model Building and Concatenation

Several classification models were created to classify the chip images and machine parameters into three classes: (a) acceptable chip (b) optimal chip (c) bad chip (Figure 2).

The hyperparameter of the SVC was tuned with the help of the scikit-learn function ‘GridSearchCV’ through an exhaustive search over specified hyperparameter space. A 5-fold cross-validation was used. A linear kernel along with ‘C’ value 1000 stopped the grid search process, for this reason, the linear kernel was removed from the candidate hyperparameter list. The grid search process for the SVC model hyperparameter took 48 hours. The final optimized hyperparameter values are provided in Table 1. Hyperparameters of the kNN and RF model were tuned with help of ‘GridSearchCV’ with 5-fold cross-validation. The grid search process for the kNN model hyperparameter took 5 minutes. The final optimized hyperparameter values are provided in Table 1.

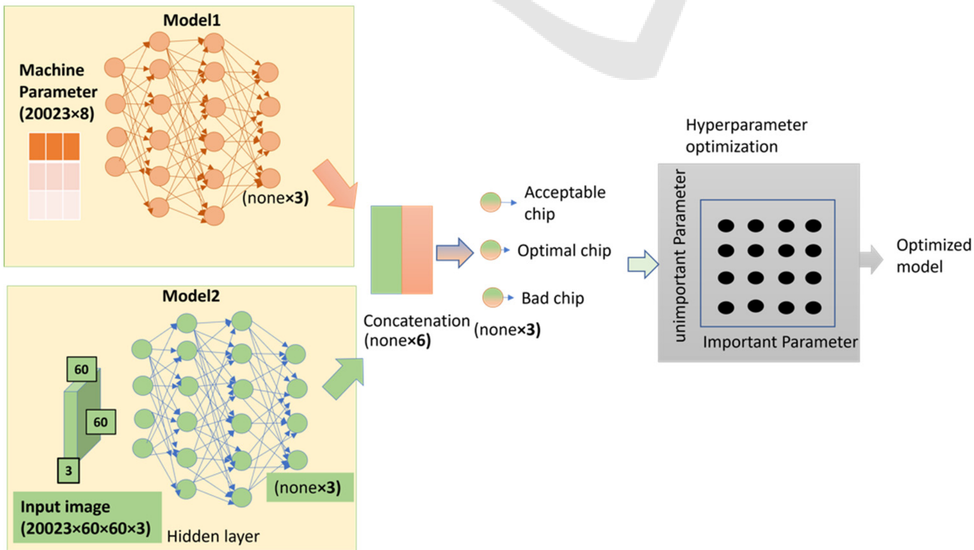


Figure 5: Concatenated model construction.

Table 1: Optimized hyperparameter values of the ML models.

Hyperparameter	**Candidate value**	**Optimized value**			
		Case 1	Case 2	Case 4	Case 5
SVC					
C	0.1, 1, 10, 100, 1000	1000	1000	0.1	1
gamma	1, 0.1, 0.01, 0.001, 0.0001	1	1	0.0001	0.001
kernel	'rbf'	'rbf'	'rbf'	'rbf'	'rbf'
Random Forest					
max depth	10, 20, 30	30	30	30	30
max features	'auto', 'sqrt'	'sqrt'	'auto'	'auto'	'sqrt'
min samples leaf	1, 2	1	1	1	1
min samples split	2, 5	2	2	2	2
n estimators	800, 1000	1000	1000	800	1000
k Nearest Neighbour					
n neighbors	5,7,9,11,13,15	5	11	5	5
Weights	'uniform','distance'	'distance'	'distance'	'distance'	'distance'
Metric	'minkowski','euclidean','manhattan'	'manhattan'	'manhattan'	'manhattan'	'manhattan'
ANN					
Learning rate	1,0.1,0.01,0.001	0.1	0.1	0.1	0.1
Activation	'relu', 'elu'	'relu'	'relu'	'relu'	'relu'
Neurons	10, 20, 30, 40, 80	40	40	40	30
batch size	16, 32, 64, 128	64	64	64	16
Optimizer	'Nadam','Adam'	'Nadam'	'Nadam'	'Nadam'	'Nadam'

Table 2: Optimized Hyperparameter values of the concrete-naked model.

Hyperparameter	Candidate value	Optimized value	
		Case 3	Case 6
Activation	'relu', 'elu'	'relu'	'relu'
Batch size	16,32,64,128	64	64
model1 neuron number	10,20, 30, 40,100	10	10
learning rate	0.01,0.1,0.001, 0.00001	0.1	0.1
dropout	0, 0.1, 0.2	0	0
Optimizer	'Adam','Nadam'	'Nadam'	'Nadam'
model2 neuron number	20,30,100, 300	30	30

In the concatenated model, three dense layers were used which is followed by a flattened layer and finally the output layer (Figure 5). At the time of training, the model 'Categorical Crossentropy' was used as the loss. After building both ANN models', the outputs were concatenated (Figure 5). The models' hyperparameters were optimized with Talos[2] . The output is the probability of a specific class. The final optimized hyperparameter values are provided in Table 2.

3.4 Deployment in Raspberry Pi

The model with significant performance was deployed in Raspberry Pi. The Raspberry Pi 4 Model B with 8GB of RAM was used in the proposed study. The Raspberry Pi can send the results of the ML model and extracted images to the Azure cloud.

4 RESULTS

4.1 Perspective 1: Change in Hyperparameter

In this perspective, change in performance with hyperparameters is focused. Table 1 shows the candidate and optimized hyperparameters while Figure 6 shows the change in hyperparameters with cases (hyperparameters that remained constant are not included in the figure).

The C value in SVC is the term used to control misclassification for hybrid architecture (Case 1 and Case 2), C in SVC has a value of 1000 while for traditional architecture (Case 5 and Case 6), the value is 1. The hybrid architecture has higher accuracy on test data with a higher C value. The penalty for misclassification is higher in the case of hybrid architecture which implies hybrid architecture considers the outliers in the case of classification. Conversely, in traditional architecture outliers are not considered. However, the test accuracy increased with the inclusion of outliers (Figure 6).

The data distributions of pixel values explain this result (Figure 7). The figure shows, for an acceptable and optimal chip the pixel values follow a normal distribution, and most data points fall within the distribution curve. However, for bad chips, pixel values do not ideally follow any distribution. The closest data distribution is the 'rayleigh' distribution.

[2]Autonomio Talos [Computer software]

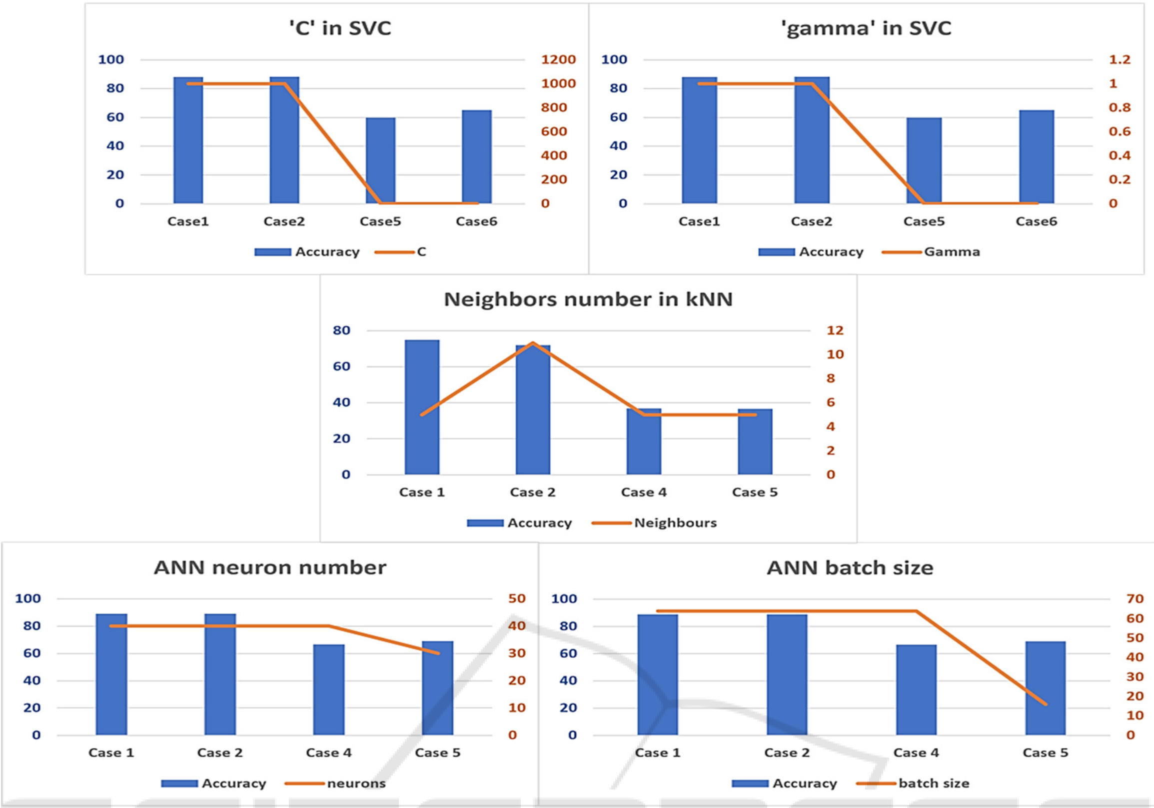


Figure 6: Change in performance with hyperparameter.

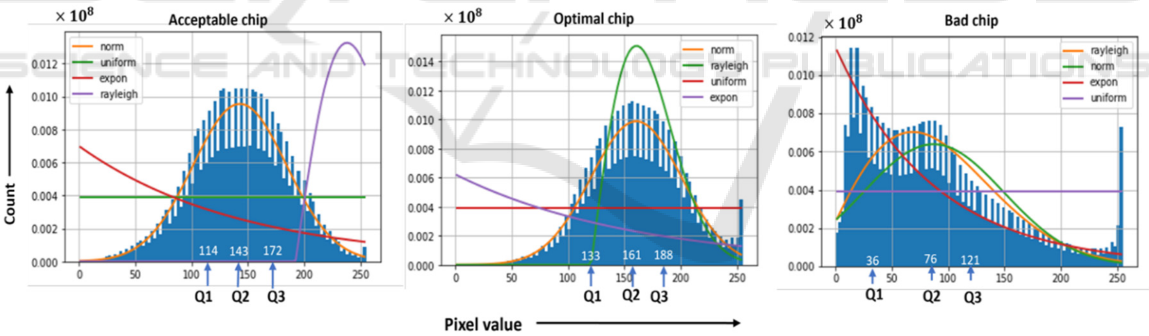


Figure 7: Data distribution of image pixels.

However, most data point shows random frequency. Considering outliers while creating the model showed success because of this distribution.

4.2 Perspective 2: Change in Architecture

In this perspective, two types of architecture such as hybrid (Case 1, Case 2, Case 3) and traditional (Case 4, Case 5, Case 6) architecture were considered (Figure 8). Hybrid architecture comprised of CNN features extractor and ML model while traditional architecture comprised of manual feature extractor and ML model. The accuracy increased by 20% because of hybrid architecture.

4.3 Perspective 3: Change in ML Algorithm

Certain ML algorithms such as SVC, RF, kNN, and ANN were used to find the best model. ANN outperformed all the other models. The accuracy increased by a factor of 15% because of the changed ML algorithm (ANN:90% and kNN:75%).

4.4 Perspective 4: Inclusion of New Data Source

In this perspective, a new data set i.e., machine parameters were used as input in addition to image data resulting in two sets of cases ((a)Only image set, (b)Image and machine parameter set). Only the image set includes Case 1 and Case 4 while the image and machine parameter set includes Case 2, Case 3, Case 5, and Case 6 (Figure 8).

Both the image and machine parameter set (Case 2) and only the image set (Case 1) have 90% accuracy. This implies the inclusion of a new data source does not increase the accuracy.

4.5 Perspective 5: Change in ANN Architecture

In this perspective, concatenated ANN architecture (Case 3 and Case 6) was compared with ANN without concatenation (Case 2 and Case 5). A concatenated ANN architecture was created to test if the changed architecture can improve accuracy in addition to the inclusion of a new data source (perspective 2). In hybrid architecture, accuracy decreased by a factor of 2% with the introduction of concatenated architecture (Case 2 and Case 3) while in traditional architecture, the introduction of concatenated architecture did not affect accuracy (Case 5 and Case 6).

Conversely, the inclusion of feature extractors such as hybrid or traditional architecture (Perspective 2: Change in architecture) changed performance significantly which indicates feature extraction can lead to the loss of significant information. To quantify the change in information aspect with change in input such as the inclusion of feature extractor and machine parameter data normalized mutual information was calculated.

Normalized mutual information considers Shanon's entropy for the quantification of change in the information aspect of one variable with the observation of another variable. In the proposed study, the added information to the true response because of the predictions from the ML models is quantified (Figure 9). As shown in the figure, 4 sets of input are considered:

- Input 1: Raw (no feature extraction) image data
- Input 2: Hybrid (feature extraction with CNN) image data
- Input 3: Traditional (manual feature extraction) image data
- Input 4: Only Machine parameter

The information bits added by the raw image is 65% while feature extractions from the raw image with CNN increased the information aspect by only 3%. Manual feature extraction decreased the information aspect by 40%. Conversely, for only machine parameters, mutual information is only 5%. This

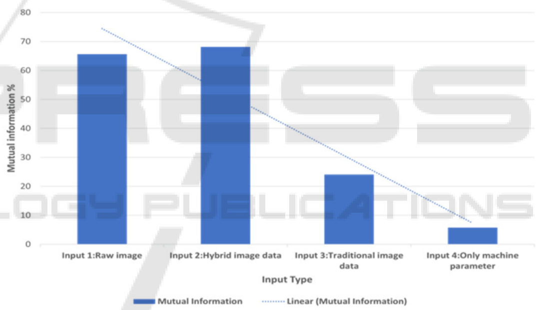


Figure 9: Mutual information associated with a different set of data.

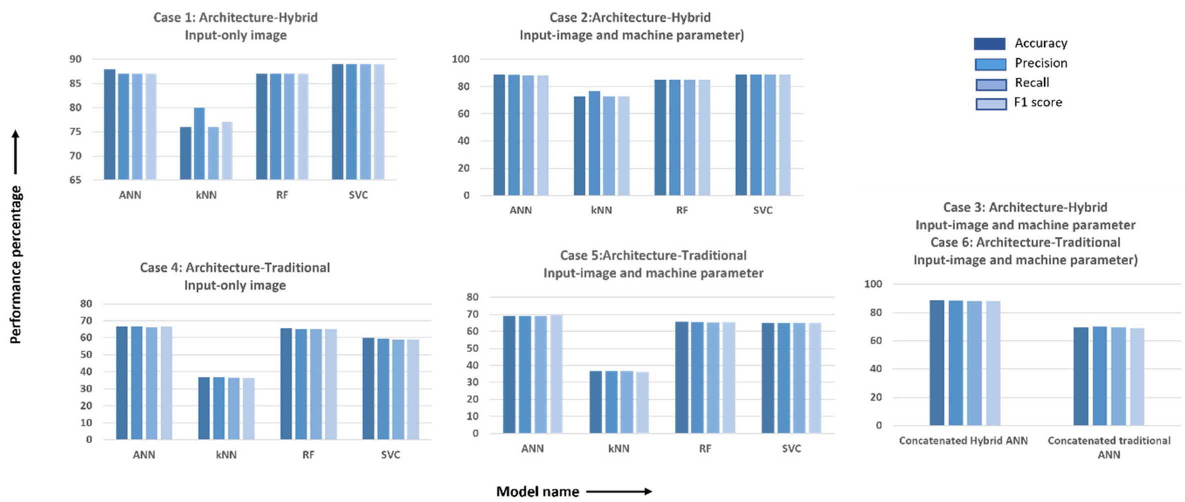


Figure 8: Change in performance with change in perspective.

explains unchanged accuracy with the addition of machine parameters (Perspective 4).

4.6 Perspective 6: Change in CNN Feature Extractor Architecture

Several research studies state deep layers such as 14 layers (Rahman, 2021), and 50 layers (Qadir, 2019) of CNN for feature extraction. However, in the proposed study it is observed that with an increment of the CNN feature extractor layer the accuracy dropped in a proportional way.

To find the reason for degraded performance the extracted features are plotted as an image for 2-layer CNN and 7-layer CNN, (Figure 10). It is shown in the figure that with an increase in the feature extractor layer the images become abstract and it loses information significant for classification.

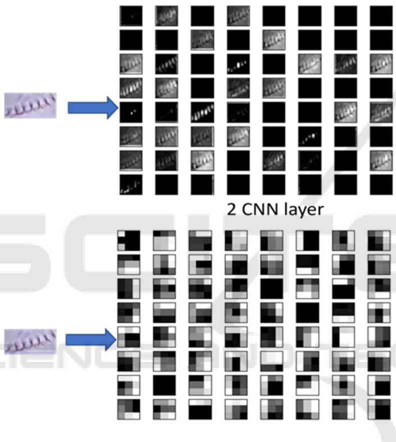


Figure 10: Chip image feature extraction with 2-layer and 7-layer CNN.

4.7 Significance Test

Wilcoxon signed-rank test is a non-parametric test used for the hypothesis test. In the proposed study, all the data do not follow the Gaussian distribution (Figure 7). For this reason, parametric test such as ANOVA was not used.

Wilcoxon signed-rank test was performed to test the null hypothesis ”The difference in true response and ML predicted response is equal to 0” The p-value for hybrid ANN (Case 2) is 0.664 while the p-value for traditional ANN (Case 5) is 0.443. Therefore, the null hypothesis cannot be rejected because the p-value is greater than the significance level alpha = 0.05. Additionally, hybrid ANN (Case 2) has a higher p-value compared to traditional ANN (Case 5) which implies hybrid ANN (Case 2) is more related to true response.

4.8 Hardware Setup Result

The complete hardware setup deployed in the manufacturing company workshop is shown in Figure 11. The microcontroller extracts frames from the video and sends them to the Azure cloud. To send 8603 frames to the azure cloud through an internet of speed 9 MB/s the microcontroller takes 8 seconds.

5 DISCUSSION AND CONCLUSION

The manufacturing industry is stepping into the era of industry 4.0 with the advancement of technology. A manufacturing system comprises numerous parts and

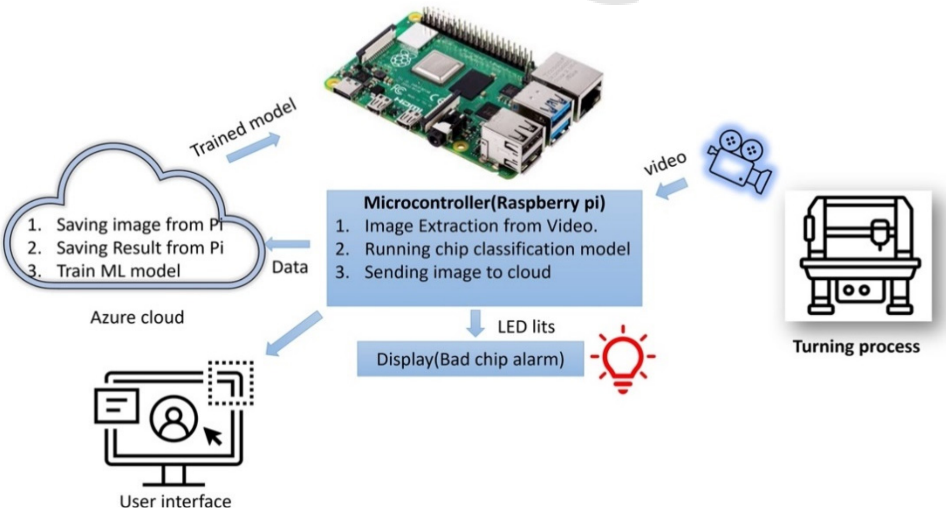


Figure 11: Complete setup in the manufacturing workshop.

malfunction of any of these parts can lead to faulty functionality. ML-integrated manufacturing can solve this problem by reducing economic loss. However, good ML performance is a prerequisite.

In the proposed study, chip images and machine parameters are used as input to several ML models for the prediction of the chip class and a quantified performance analysis from six discrete perspectives was performed.

One of the findings of the proposed study is that SVC, kNN and ANN are the top three ML models which are affected by hyperparameters significantly. The C value of the SVC classifier is an indication of data distribution. A significant C value indicates the presence of an outlier. Additionally, accuracy can be increased by a factor of 30% with hyperparameter tuning.

However, ML performance improvement can be a paradox. In the proposed study, the initial target was to achieve an accuracy above 90%. For this reason, hyperparameters were tuned increasing accuracy by 30%. For further improvement, automatic feature extraction with CNN instead of traditional feature extraction was implemented which increased the accuracy by a factor of 20%.

Several state-of-the-art ML models such as SVC, kNN, RF and ANN are trained to find the best-performing model. Changing the ML model increased the performance by a factor of 15%. The best-performing model is ANN.

The findings of the proposed analysis show that an increment of data which does not contribute any information will not increase performance. The pitfall of data is the widely accepted belief ”more data means better performance”. However, more data does not always lead to better performance. An added data source only increases performance if the posterior probability of the response variable changes significantly with the inclusion of a new data source. Additionally, the concatenation two ANN model will contribute to better performance only if the input data quality is better. Therefore, data plays a significant role compared to model architecture.

A significant number of scientific publications show performance increment with the extraction of features such as edge, and colour. However, the analysis based on perspectives 5 and 6 shows feature extraction does not always contribute to model performance increment. In certain cases, feature extraction can suppress information significant for classification. For this reason, raw pixel values have a similar performance as the CNN extracted features.

It can be concluded that an industrial case study can have a distinct characteristic which can lead to the failure of popular performance improvement methods. In the proposed study, the detected objects (chips) can be a few millimetres resulting decrease in accuracy with feature extraction compared to raw pixel values. Additionally, it can be concluded that data quality plays the main role in performance improvement compared to hyperparameter tuning, model architecture changing, feature extraction method, size of data, and algorithm selection. The ML model predictions are not produced by chance (according to Wilcoxon signed-rank test).

The limitation of the proposed study is the latency introduced due to image processing leading to limited application for real-time object detection. The findings of the proposed study apply to the specific case study and case studies with similar types of data. In future, the same analysis can be performed on benchmark data sets to draw a more generalized conclusion.

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