Root Cause Classification of Temperature-related Failure Modes in a Hot Strip Mill

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Abstract: Data is one of the most valuable assets a manufacturing company can possess. Historical data in particular has much potential for use in automated data-driven decision-making which can result in more efficient and sustainable processes. Although the technology and research behind data-driven systems for Root Cause Analysis has developed vastly over decades, their use for real time automated detection of root causes within steel manufacturing has been limited. Typically, root cause analysis still involves a lot of human interaction both in the pre-processing and data analysis phases, which can lead to variability in results and cause delay when devising corrective actions. In this paper, an application for automated Root Cause Analysis in an Hot Strip Mill is proposed for the purpose of demonstrating the effectiveness of such an approach against a manual approach. The proposed approach classifies temperature defects of steel strip Width Pull using a variety of machine learning algorithms in conjunction with k-fold cross validation.

1 INTRODUCTION

Each year, millions of tonnes of steel are rolled by steel companies across the globe. While steel-making plants strive to produce high quality steel strip and limited waste, various defects still occur on a regular basis and thousands of these are recorded by operators each year. Width-related defects account for a large portion of these.

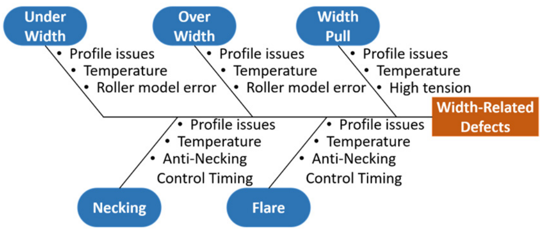

Figure 1: A fishbone diagram showing the causes of Width Pull throughout an HSM.

There are several width-related defects, each with a number of failure modes with potential origins from various Hot Strip Mill (HSM) sub-processes, including bar specification issues, temperature fluctuations, and erratic tension control.

The current procedures used to determine the causes of width-related defects, however, are mostly manual and require human interaction before the issue can be resolved, sometimes even including simple true or false condition checks. This creates an inconsistent timescale in which defects may go unrecognised and successive products are therefore negatively affected. These problems can occur not only when defective behaviour is identified at a later time, but also if defective behaviour is missed and therefore goes unrecorded. Although human error is thought to be the main concern associated with manual processes, fast-paced and critical decision-making and resource allocation are also primary concerns (Janssen et al., 2019; Sheridan & Parasuraman, 2000).

In recent decades, root cause analysis (RCA) methodologies have adopted more up-to-date and relevant technologies including automation and machine learning (Mahto & Kumar, 2008). Automation has proven to be a powerful approach in manufacturing operations and RCA, dramatically reducing the time between the occurrence of physical events and digital analysis and visualisation (e Oliveira et al., 2022), usually without the need for

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human interaction. Machine learning also enables RCA systems to learn patterns in data which can be too ambiguous for a human to perceive and provides the ability to re-train a system to adapt to new or unforeseen behaviour (Wiering & van Otterlo, 2012; Wuest et al., 2016). Within the steel rolling industry, RCA, particularly with machine learning, is not yet mainstream outside of its use in applications for surface defect detection and roller model optimisation. Currently, such applications have also not been embedded into a larger RCA system spanning multiple sub-processes in an HSM, which is a future aim of this study.

By increasing the scope of machine learning applications in an HSM setting, it is possible to create a broad set of RCA tools for the identification of failure modes which can be used to improve the current process and reduce workload on team members, allowing them to focus on other more meaningful tasks. In the future, it would also be beneficial to combine these tools into a broad system to identify both the cause and origin of a defect throughout a number of HSM sub-processes. This would provide quick access and a simple but detailed overview of the process with regards to process performance and RCA.

In this paper, a proposition is made for an automated RCA application which utilises machine learning to classify the root cause of Width Pull in an HSM. This aims to show that there is potential for a series of this type of application to be created in a steel industry setting and, in future, compiled into a final system which can broadly monitor the HSM process. The resulting application aims to save time and boost productivity of both the HSM process and analysts and reduce the overall number of defects that occur in the future. In section 2, an insight into the current issues and analysis procedures used in existing HSMs is highlighted and a deeper understanding into the background of RCA systems and machine learning both in general and in the steel industry is provided. The data pre-processing steps taken and the methodology used to carry out classification experiments are then outlined in section 3. The results of these experiments are then evaluated against a manual approach to the described problem in the penultimate section before concluding on the proposed approach's performance, the optimal machine learning model, and how it might be improved in the final section. Future work aims to discuss the need and integration of such an application in a broader RCA system spanning the entire HSM process. This will be in conjunction with a previous work in which an RCA application was created for failure mode classification in an HSM (Latham & Giannetti, 2021).

2 BACKGROUND

2.1 Root Cause Analysis in Manufacturing and the Steel Industry

2.1.1 Early Stages of Root Cause Analysis

Having only been around since the 1950s and only becoming mainstream after the creation of Lean 6 Sigma in the 1980s, RCA has played a major part in the push towards a better understanding of faults that occur in manufacturing processes (Arnheiter & Greenland, 2008; Ohno & Bodek, 1998). The aim of RCA was originally to identify the cause of a known issue so that an appropriate solution can then be determined. However, the methodologies used to achieve this goal has evolved over the years (Arnheiter & Greenland, 2008) to make this process more streamline and beneficial. Some examples include the inclusion of expert knowledge, prescribed solutions and, more recently, automation (Diez-Olivan et al., 2019; Giannetti et al., 2015).

The first major example of a practical RCA approach was the use of the 5 Whys methodology, created in the 1930s by Toyota engineers (Serrat, 2017), but becoming popular later in the century as part of the Lean 6 Sigma framework . While Lean 6 Sigma is used to improve general business efficiency, its techniques are often applied in the manufacturing industry (Sreedharan & Raju, 2016). The 5 Whys approach encourages further investigation into why faults occur (Serrat, 2017), which, as mentioned, is the main aim of RCA. The next major step in developing RCA was to further include expert knowledge such that analysts could make a guided diagnosis of the issue (Sarkar, Mukhopadhyay, & Ghosh, 2013). These expert systems eventually included further knowledge such that a prescribed solution could be given depending on the diagnosis and inputs (Cao et al., 2022; Kalantri & Chandrawat, 2013). These were the first major steps towards introducing artificial intelligence into RCA methodologies.

2.1.2 Root Cause Analysis and Machine Learning

Over the last few decades, the amount of data collected in manufacturing processes has been increasing at such a rate that it is becoming an increasingly important challenge to make use of this data in an efficient manner (Yaqoob et al., 2016). However, the infrastructures in which such vast amounts of data are stored are often unorganised and require a number of processing steps (Madden, 2012) before data is transformed into a suitable standard for analysis. The inclusion of artificial intelligence has propelled the development of RCA tools and methodologies such that it is now possible to quickly and efficiently process large amounts of information. There are many examples which demonstrate such tools which include the use of neural networks, regression models, and other more traditional analysis models such as control charts for automated RCA in a variety of industries (Oliveira et al., 2022; Giannetti et al., 2014a, 2014b). However, some argue that further development is still required to maximise its potential (Zhang et al., 2020).

In the last several decades, machine learning has become a very popular tool for quick and automated analysis and feedback in manufacturing processes (Cinar et al., 2020; Dogan & Birant, 2021; Essien & Giannetti, 2019; Giannetti & Essien, 2022). The premise of machine learning is to learn patterns from the features of a given set of historical data and use this information to create a model that can identify these patterns in new, unseen data. This approach attempts to automate manual RCA operations and provide quick, if not immediate, feedback (Steenwinckel, 2018).

There are many applications of RCA which utilise machine learning in the manufacturing industry (Weichert et al., 2019), and many unique approaches have been taken to develop them. One such example is the use of machine learning-based anomaly detection methods, including K-Nearest Neighbour (KNN) and Local Outlier Factor (LOF), to detect failure modes in assembly equipment (Abdelrahman & Keikhosrokiani, 2020). Another application includes the use of machine learning, specifically neural networks, for quality monitoring in an injection moulding process (Nam, Van Tung, & Yee, 2021). One more example is the use of supervised methods such as K-Means Clustering and decision trees for the detection of root causes of defects in semiconductors (Tan et al., 2021). It is worth noting that some approaches argue that a knowledge-based approach can sometimes be more suitable than machine learning depending upon the scenario (Martinez-Gil et al., 2022; Roshan et al., 2014). It is clear that some solutions are chosen to cater to the use case addressed by the application but have the common goal of using information from a process to provide useful feedback for the purpose of improving a process (Weichert et al., 2019).

2.1.3 Root Cause Analysis in the Steel Rolling Industry

Within the steel rolling industry machine learning and, especially, RCA is not yet mainstream and has only seen analytics for RCA used on a niche scale. While there has been much development for existing applications of machine learning, areas of focus in research are largely limited to surface defect detection (Huang, Wu, & Xie, 2021**)** and roller model optimisation (Li, Luan, & Wu, 2020). While it may be difficult to introduce new technologies into an operation of such a scale, machine learning has untapped potential with regards to RCA in the steel industry as it would enhance the automation of such analyses. Time and resources spent on conducting this process manually would therefore be saved and workers who would normally be tasked with this could devote more time to other workloads or more complex projects in which human interaction is a necessity.

2.2 Width Pull and Current HSM Procedures

2.2.1 Width Pull in the HSM

When Width Pull occurs, the head end of a steel bar either elongates or becomes under width specification as a result of sudden tension in the strip (Khramshinet al., 2015; Radionov et al., 2020). This defect can occur for an array of reasons, including wrong bar specifications, high or low temperatures, and erratic tension.

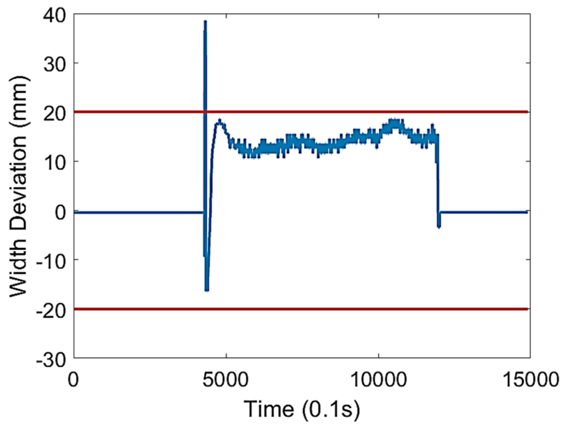

Figure 2: A graph showing the width deviation of a strip with Width Pull.

Currently, when Width Pull occurs in the HSM, the root cause is determined via a manual analysis of the defective sample. There are many causes of Width Pull and, although there is a workflow in place to determine basic causes, the data examined to determine other causes can be quite ambiguous making them difficult to draw conclusions on. Although temperature-related causes normally originate from the furnace (as shown in Figure 3), it is important to note that the issue is originally identified in a later part of the HSM process such as Roughing or Finishing. Many failure modes of width-related defects in the HSM process are temperature-related (as shown in Figure 1).

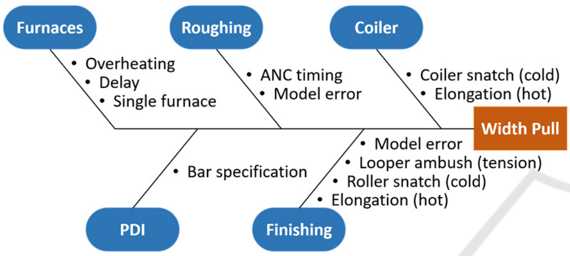

Figure 3: A fishbone diagram showing the causes of Width Pull throughout a HSM.

2.2.2 Current HSM Procedures

Width Pull, as well as other defects that occur in the HSM, can have damaging effects both in the short-term and long-term. Depending on the severity of the under width caused by Width Pull or other defects, a follow-up action is carried out. The first possible action is a cutback in which the under width portion of the strip is cut off. This results in a shorter strip length and scrap which is melted for use in later strips, requiring further processing which is both time-consuming and unresourceful. Another action is to make a concession in which the customer is offered the defective strip at a negotiated lower price. Although this action does not always require further processing, potential profit is still lost. This however does not mean that cutbacks do not occur before or after concessions are made. In the worst-case scenario, the strip is scrapped altogether. In the long-term, all follow up actions require either further resources and cost time and money, or result in wasted material, ultimately producing business waste (Sarkar, Mukhopadhyay, & Ghosh, 2013; Sreedharan & Raju, 2016).

The effects of these defects can also be derived not just from the defect itself but from the manual analysis process that is currently used to determine their root causes. Issues are often caught or resolved long after immediate and, sometimes, lasting impacts that are created by defective behaviour. For example, some causes of Width Pull can affect a sequence of strips if left unresolved (Khramshin et al., 2015). A build-up of unresolved issues also suggests that the information collected about root causes is analysed too late to have a meaningful impact on the process, resulting in a less productive system. Lastly, manual analysis is time-consuming for analysts themselves. It is a trivial task which, if automated, would enable them to focus on more complex tasks and other responsibilities, thus boosting their productivity.

3 METHODOLOGY

3.1 Problem Statement

In the following experiments, the potential of machine learning for automating RCA in an HSM setting is demonstrated by classifying temperature-related failure modes of steel strips which have suffered from Width Pull. This application is planned to be part of a greater work which will combine such applications and determine the failure mode and origin of identified strips with Width Pull throughout the HSM.

3.2 Dataset

The number of steel strips affected by low temperature, or 'undersoaking', accounts for a larger percentage of samples, overall making the dataset used in this study unbalanced. At the time of data collection, a total of 166 samples were available, 111 of which were undersoaked and 55 of which were high temperature. Despite the imbalance, the available dataset still had a limited number of samples. It was therefore decided to use the whole dataset for this experiment rather than reducing the amount of undersoaked samples to account for balance, which would limit the quality of training during machine learning.

Table 1: A table showing the split of labelled data used in this experiment.

	Training Dataset	Testing Dataset	Total (Label)
Undersoaked	78	33	111
High Temp	39	16	55
Total (Dataset)	117	49	166

Each sample is derived from two temperature signals which are pre-processed and compared to evaluate their representation of the root cause. This is achieved through a series of transformations which eliminate redundant data and account for differing temperature ranges between different product specification and comparing the range of values between different product specifications and comparing the range of values between the two signals following these transformations. Statistical features are then chosen to represent the samples during the training stage of machine learning. These features help the chosen machine learning algorithms to distinguish between the behaviour of undersoaking and high temperature.

3.3 Pre-processing and Labelling

In order to analyse the signal data both manually and using machine learning, redundant data must first be eliminated and, if it is not already, the remaining data must be processed into a readable format. By cleaning signal data like this, a more relevant perspective of our data is shown, making data from different classes more distinct during the feature extraction stage. The first step is to eliminate irrelevant measurements in the signal which occur when the bar is not present in the Finishing Mill (as shown in Figure 4). A binary Metal-In-Mill (MIM) signal displays whether or not the bar is present in the mill. The second step is completed by extracting the temperature signal measurement where the MIM signal is activated (as shown in Figure 5).

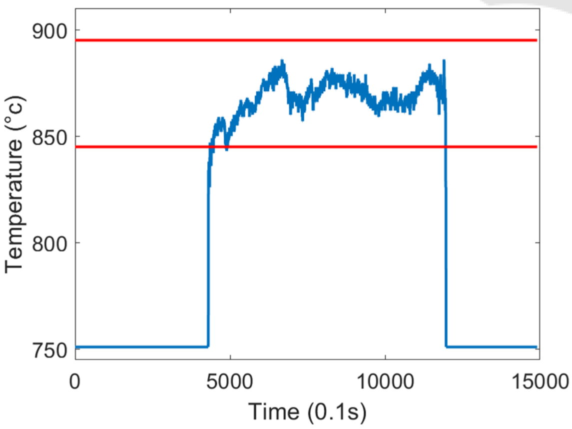

Figure 4: Temperature signal of an undersoaked strip before pre-processing.

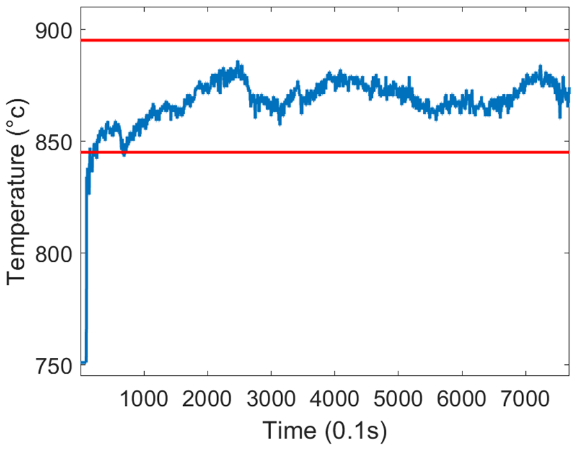

Figure 5: Temperature signal of an undersoaked strip where MIM signal is activated.

The second step is to pad outlier measurements to sensible values (as shown in Figure 6). Measurements above a strip temperature's upper tolerance plus 50°c are set to this value. Alternatively, measurements below a strip temperature's lower tolerance minus 50°c are set to this value. Outlier values alone are not enough to distinguish whether Width Pull is caused by temperature. This is because these values may be caused by erroneous sensor readings and, very commonly, noise upon the strip's entrance into the Finishing Mill. Data representing this behaviour is therefore eliminated from the beginning of the signal to remove redundant values that may misrepresent failure modes during training.

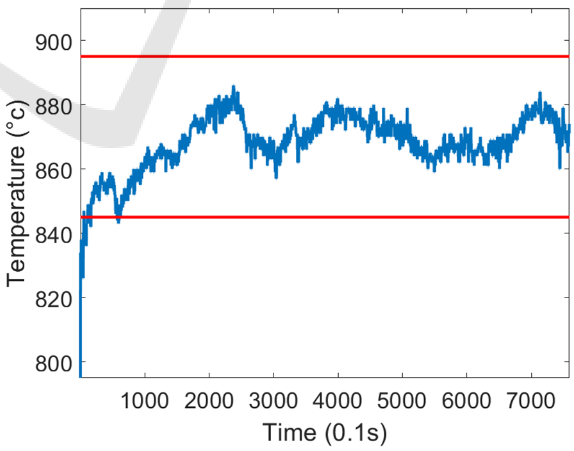

Figure 6: Temperature signal of an undersoaked strip after outliers are removed.

The next step in narrowing down on this information is to segment first 10% of the signal, representing the head end of the strip (as shown in Figure 7). This is because Finishing Mill Width Pull instances typically occur in the head end of the bar. The final step maps each signal to a comparable scale such that measurement ranges are mapped to the sample values. A standard peak normalisation formula (1) is used with the minimum and maximum values of each signal to map all values of all signals between 0 and 1 (as shown in Figure 8).

$$Peak\ Norm. = \frac{x - \min_n(x)}{\max_n(x) - \min_n(x)} \qquad (1)$$

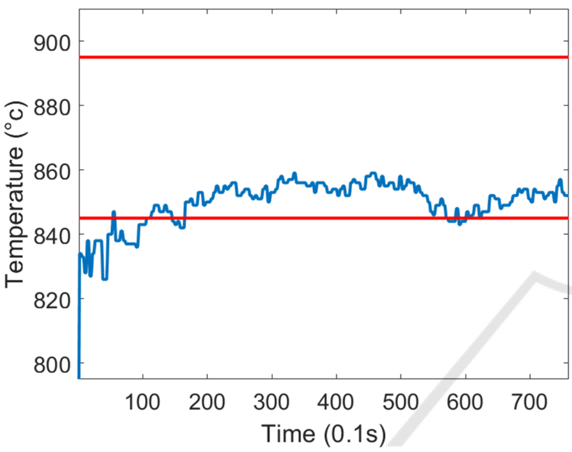

Figure 7: Temperature signal representing the head end of an undersoaked strip.

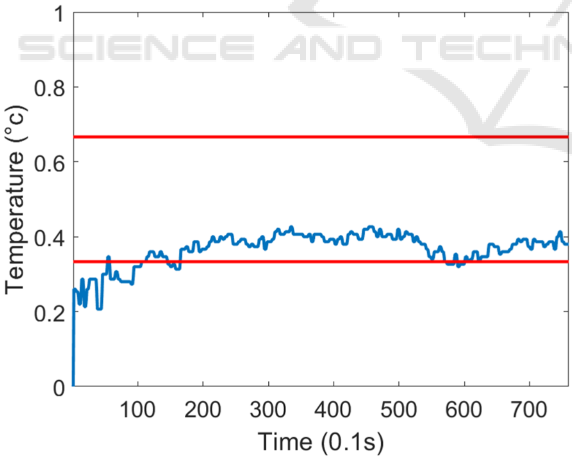

Figure 8: Temperature signal of an undersoaked strip after peak normalisation.

Although basic labels exist to show simply whether or not a steel strip sample is has Width Pull, the data required for this application must be specific to the root cause of the defect. Using a combination of the existing manual analysis process, the extracted data, and a series of plots displaying the now cleaned signal data, the root causes of the extracted Width Pull samples were manually labelled, creating further labels used to train and test the final machine learning algorithms.

3.4 Feature Selection

A collection of statistical features was extracted from the pre-processed data for use in the chosen machine learning algorithms. These include several quartile values, mean, peak value, root mean square, and standard deviation. Pearson's Correlation Coefficient was then used to determine which of these features would be used during training. More specifically, the averages of each feature after being applied to this formula were used as a guide to eliminate features which correlated too closely and would therefore become redundant or counterproductive during training (Schober, Boer, & Schwarte, 2018). The result of this methodology is a feature set which is combined with the labels to create a final dataset which can be used to train and test the machine learning model appropriately.

3.5 Machine Learning Algorithms

A variety of classic machine learning algorithms has been selected for training and testing in this experiment. This subsection briefly describes each model and their parameters.

3.5.1 Trees

A classification tree is a linear graph in which each node is assigned a value based on training features. These values are used as a foundation for decision-making when classifying new samples.

3.5.2 Naïve Bayes

Naïve Bayes also uses probabilities based on training features to determine classification labels. However, the Naïve Bayes algorithm bases these probabilities on the frequency of each value, meaning that more prominent features are dominant in classification.

3.5.3 K-Nearest Neighbour

The KNN algorithm creates a dimensional space in which samples are plotted based on the values of their features. New samples are plotted in this space and compared to a chosen number, k, of neighbours. The class of a new sample is chosen based on the class of the majority of its k neighbours. It should be noted that the numbers k in KNN and k-fold cross validation are unrelated.

3.5.4 Support Vector Machines

A Support Vector Machine (SVM) also plots feature values into a dimensional space, although rather than comparing new samples to a distribution, this algorithm attempts to create a new, separating hyperplane. New samples are classified based on their position relative to this hyperplane.

3.5.5 Artificial Neural Networks

Artificial Neural Networks (ANNs) are made up of neurons which are combined to form a number of layers. Each neuron has a weight which is updated during training based on the inputted features. An ANN's width and depth is determined by the number of neurons and layers it contains.

3.5.6 Ensembles

An ensemble combines the result of more than one machine learning algorithm. The ensembles used in this experiment combines several tree algorithms.

3.6 K-fold Cross Validation

K-fold cross validation is used to estimate the generalisation error of a machine learning model. In this experiment, $k = 5$ has been chosen such that each machine learning algorithm is run five times using 80% of the training dataset. For each of the five runs, 20% is not used during training.

4 RESULTS

4.1 Full Training Dataset

A total of 13 machine learning algorithms were used in the training stage of this experiment. Accuracy, precision, recall, and F1 score metrics are used to evaluate the performance of each model. Accuracy simply calculates the overall percentage of correctly labelled samples. Precision describes the percentage of samples which are labelled as a given class that truly belong to this class while recall describes the percentage of samples which belong to this class that are classified correctly. Although accuracy is still an informative metric, F1 score is derived from precision and recall, and evaluates the performance of classification models more reliably. In the following results, F1 score is represented as a percentage for consistency among metrics.

Table 2: Performance of each machine learning algorithm when trained on the full training dataset.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Coarse Gaussian SVM	93.88	88.24	93.75	90.91
Coarse Tree	**95.92**	**93.75**	**93.75**	**93.75**
Fine Gaussian SVM	81.63	81.82	56.25	66.67
Fine KNN	87.76	85.71	75	80
Fine Tree	**95.92**	**93.75**	**93.75**	**93.75**
Gaussian Naïve Bayes	93.88	84.21	1	91.43
Kernel Naïve Bayes	95.92	88.89	1	94.12
Linear SVM	91.84	87.5	87.5	87.5
Narrow ANN	93.88	93.33	87.5	90.32
Opt. Ensemble	91.84	87.5	87.5	87.5
Opt. ANN	93.88	93.33	87.5	90.32
Quadratic SVM	91.84	87.5	87.5	87.5
Wide ANN	89.8	86.67	81.25	83.97

From the results shown in Table 2, it can be seen that a majority of the trained models can be used appropriately for the classification task. However, only a handful show consistent scores between the performance metrics. In particular, the Coarse and Fine Tree models have been shown to perform best with accuracies and F1 scores of above 93%. These models are generally quick to train and thus easier to retrain when more data becomes available. Although the Kernel Naïve Bayes model provides a better accuracy, recall, and F1 score, its precision falls behind the two Tree models, suggesting it does not perform as well when labelling a particular class.

4.2 K-fold Cross Validation

After 5-fold cross validation, the models show slightly decreased but similar performance to the previous test results (as shown in Table 3). This means that although each algorithm was given less information during training, the models were still able to generalise data relatively well, resulting in stable training and thus reliable and consistent models.

Table 3: Performance of each machine learning algorithm in 5-fold cross validation.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Coarse Gaussian SVM	85.31	79.01	75	76.88
Coarse Tree	**88.37**	**83.8**	**80**	**81.73**
Fine Gaussian SVM	87.89	82.78	79.58	81.06
Fine KNN	88.16	82.55	80.94	81.63
Fine Tree	**88.82**	**83.76**	**81.75**	**82.62**
Gaussian Naïve Bayes	88.64	82.59	83.13	82.64
Kernel Naïve Bayes	88.57	81.94	83.93	82.7
Linear SVM	88.47	81.76	83.75	82.55
Narrow ANN	88.57	82.55	83.19	82.54
Opt. Ensemble	**88.86**	**82.69**	**84**	**83.03**
Opt. ANN	88.79	82.47	84.09	82.98
Quadratic SVM	88.74	82.46	83.85	82.87
Wide ANN	88.73	82.72	83.46	82.78

While it is beneficial to determine whether a machine learning model generalises well, as has been shown in this experiment, the Tree-based models would be likely to be selected for use in this application based on their superior performance in the full training experiment (as shown in Table 2). In this particular cross validation experiment, the Optimisable Ensemble performed marginally better than other models, but would not be selected for use in the final application based on its performance when trained on the full dataset.

At the current time, the small dataset used in this experiment is suitable for the application of classifying temperature-related root causes of Width Pull. However, using the best performing machine learning algorithms in this experiment, it will be both time and cost-efficient to retrain with more data at a later date.

5 CONCLUSION

A digitised version of the current RCA system for Width Pull in an existing HSM has been proposed and has shown to perform acceptably for the given task. It is capable of providing almost immediate results and feedback, dramatically reducing the time between a defect occurring and its root cause being identified.

There would be several benefits of adopting this application into an HSM setting. Time would be saved on performing unnecessary analyses, reserving efforts for productivity elsewhere. This application also showcases the potential of combining data sources with the aim of repurposing data to create new tools and maximise the value of data resources. This application is a step towards further automation and digitisation of basic HSM analyses and shows this approach has the potential to reduce workload on analysts such that human interaction can be directed towards more complex issues in the HSM. In future work, there may also be potential in applying this methodology to other steel strip manufacturing processes, such as casting and cold rolling, and linking the analyses of root causes between these processes.

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