

Quality Prediction Based on Artificial Neural Networks in the Plastic Injection Molding Process

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Abstract

This study proposes a data-driven approach for predicting product quality in plastic injection molding based on actual manufacturing data. The dataset comprises 500 production observations, including 461 non-defective and 39 defective products. The data were divided into training and testing sets using an 80:20 ratio, with SMOTE applied exclusively to the training set to mitigate the substantial class imbalance. Regression analysis was subsequently conducted to identify the most relevant process parameters from five candidate variables. This analysis identified melt end point and melting time as statistically significant predictors, which were then used to develop three classification models: Backpropagation Neural Network (BPNN), Random Forest, and Support Vector Machine. Each model was evaluated over ten experimental repetitions, with Accuracy and AUC serving as the primary performance measures, while Precision, Recall, F1-score, and confusion matrices provided additional evaluation. Across the experiments, BPNN produced the strongest overall predictive performance. The main contribution of this study is the integration of statistically informed feature selection and imbalance treatment with computationally lightweight machine-learning models, demonstrating a practical approach to quality prediction when only a limited amount of real-world manufacturing data is available.



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1. INTRODUCTION

Pulling together numerous ever-evolving elements of advanced technology including high-precision sensors, complicated cyber-physical systems, an immense cloud-computing scope, expansive data analytical paradigms and trades among various different intelligent machine learning algorithms in this way orchestrating Industry 4.0 is obviously enabling the most unprecedented and radical transformation enroute to the manufacturing sector as a sustainable whole. This sweeping technological transformation is critical and necessary in a highly specialized field like plastic injection molding operations. The greater level of importance for quality assurance is attributed to the fact that final product quality typically consists of a multitude, dynamically interacting process parameters so that any single measure can only ensure an effect generalized quality assurance effect [1]. These important process parameters, which continuously affect one another and should be managed effectively during the production steps include melt temperature, holding pressure, cooling time, mechanical screw position and full manufacturing cycle time [2]. The relationships among these parameters are often nonlinear, making them difficult to map solely through manual inspection or operator experience-based rules.

Plastic injection molding is one of the primary processes in the plastics industry due to its capability to produce products with complex dimensions and high productivity [3]. However, increased productivity

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does not necessarily guarantee quality stability. Products may experience defects such as short shots, flash, warpage, non-glossy surfaces, or deformation [4]. If defects are not detected from the outset, the costs associated with internal and external failures will increase, including scrap, rework, delivery delays, and a decline in customer satisfaction [5].

Manual inspection is still widely employed in traditional factories due to its ease of implementation and the absence of a need for high technological investment. However, this method has limitations in detecting small defects, recurring defect patterns, or gradual process changes [6]. Therefore, a data-driven quality control approach is required, one that can rapidly and objectively interpret process patterns.

Newer machine learning techniques have been utilized and expanded upon more rigorously as a stronger means of accurately predicting quality than traditional methods, largely because machine learning approaches can autonomously learn, interpret and model the extremely complex, non-linear relationships that always exist between measurements taken from process data arising from complex manufacturing processes and the final product quality state over time [7]. Many academic investigations and experiential analysis have experimental evidence to confirm a variety of sophisticated modeling methods; such as artificial neural network, decision trees (DT), random forest (RF), and support vector machines (SVMs); revealed that these methods can be relied upon for highly predictive performance in predicting key design attributes about injection molding processes [8]. Nonetheless, effectively implementing and smoothly embedding such sophisticated forecasting frameworks into the complex, reality-based workings and open-ended settings of real-world factories are frequently high stakes, multi-faceted problems to crack. Some of these practical roadblocks face each other in a consanguine, irritating loop related to the accessibility and reproducibility of legacy data; the characteristically possible scientific class-imbalance problem with industrially-prepared datasets; and an essential need for producing interpretable models that can be painstakingly analyzed by human quality engineers who shall end up being assigned to guarantee steady improvement of a manufacturing operation on the manufacturing shop floor [8].

Considering the theoretical and practical background outlined above, this paper systematically formulates a holistic quality prediction framework using in-depth regression analysis methods combined with SMOTE followed by a comprehensive comparative study on three different machine learning models. Thus, statistical regression analysis is intentionally applied as an enabling technology for feature selection in this analytical pipeline where process parameters with the most direct correlation to final product quality are distinguished from all other signals. At the same time, SMOTE is effectively utilized in adjusting data distribution to prevent any bias by the algorithm from favoring a class that has a higher representation during machine learning. Finally, extensively compare three state-of-the-art predictive algorithms (Back Propagation Neural Network (BPNN), Random Forest (RF) and Support Vector Machine (SVM)) in the comprehensive predictive data processing step. Finally, the performance of the three algorithms was compared using Accuracy and AUC as the main evaluation metrics. Accuracy reflects the proportion of correctly classified observations, whereas AUC assesses the model's ability to distinguish defective products from non-defective ones across varying classification thresholds. Given the imbalanced nature of the dataset, AUC provides a useful complement to Accuracy by offering a broader assessment of the models' discriminative capability. Additional evaluation measures, including Precision, Recall, F1-score, Specificity, and confusion matrices, were included to examine classification errors in greater detail, with particular attention to the models' ability to identify defective products.

The focus of this project is on accurately identifying and classifying the key process parameters that have a measurable and significant influence over the quality characteristics of finished goods plastic injection molded parts. Secondly, it aims to develop highly accurate prediction models based solely on real-world production data with the above BPNN, RF and SVM architectures. Third, the research will use various statistical evaluation metrics to comprehensively appraise the prediction performance and reliability of these developed models based on overall accuracy, AUC, confusion matrix, precision, recall and harmonized F1-score. Ultimately, the study aims to distill these analytical insights into actionable strategies on the pragmatic deployment of the best predictive model, thus ushering a new era of smarter quality inspection in contemporary manufacturing.

The originality of this study stems from the combination of statistical feature screening, SMOTE applied exclusively to the training data, and a comparative assessment of lightweight machine-learning models using real-world production data from plastic injection molding. Instead of incorporating numerous process variables or adopting highly complex model architectures, the study examines whether two statistically significant parameters, namely melt end point and melting time, are sufficient to support reliable product-quality prediction. This focus addresses a practical challenge in manufacturing settings

where historical production records are limited, and predictive solutions must balance model performance with simplicity and ease of implementation.

2. LITERATURE REVIEW

2.1 Plastic injection molding and quality challenges

Injection molding is widely utilized for the production of plastic components in the automotive, electronics, household, packaging, and medical equipment industries [9]. This process encompasses the melting of the material, injection into the mold cavity, pressure holding, cooling, product ejection, and post-production procedures. The final product quality is influenced by material characteristics, mold design, machine settings, temperature stability, and operational conditions throughout the production cycle.

In practical processes, defects may arise due to a combination of several causes. Incomplete products can result from excessively low material temperature, inadequate injection pressure, or insufficient injection time [10]. Flash and warpage can occur due to excessive pressure, prolonged holding time, or unfavorable parting line conditions. Deformation is often associated with imperfect cooling, product thickness imbalance, or uneven flow distribution [11].

Thus, quality control in injection molding is not sufficient by merely inspecting the final product. Factories need to monitor process parameters to identify patterns that may potentially cause defects. Machine learning can assist engineers in correlating variations in process parameters with product quality status, enabling more rapid collective decision-making [8]

2.2 Machine Learning for Quality Prediction

Machine learning is a branch of artificial intelligence that enables computer systems to learn patterns from data without explicitly programmed rules. In quality prediction, machine learning utilizes process variables as inputs and quality status as outputs. The model then learns historical patterns to predict whether new products are likely to meet specifications or potentially be defective [12]. Previous research indicates that machine learning is effective in injection molding because process data is typically multivariate and interrelated [13]. Decision tree-based models can operate efficiently on tabular data, whereas neural networks are capable of capturing nonlinear patterns [14]. SVM is also relevant for limited datasets as it seeks to construct a hyperplane with an optimal margin between classes [15]. Although more complex models such as deep learning and transformers are increasingly utilized, lightweight approaches remain essential for industrial applications. Factories with limited data, computational constraints, or the need for rapid implementation require models that are sufficiently accurate, easy to retrain, and capable of integration with existing control processes [16].

2.3 Handling imbalance data with SMOTE

In quality inspection, the number of defective products is typically much smaller compared to good products. This condition is referred to as class imbalance. If a model is trained directly on highly imbalanced data, it tends to predict the majority class and fails to recognize the defective class. Consequently, the overall accuracy may appear high, but the ability to detect defects becomes low [17]. SMOTE is employed to generate synthetic samples in the minority class through interpolation between neighboring minority observations [18]. In this study, SMOTE was applied exclusively to the training data after the data split. This step is crucial to maintain the validity of the evaluation, as the test data continues to contain actual production observations rather than synthetic data.

2.4 BPNN, Random Forest, and SVM

The backpropagation neural network is a multilayer artificial neural network that learns by updating weights based on prediction errors. This model is suitable for injection molding because it can capture the nonlinear relationships between process parameters and product quality [19]. The model generates predictions through forward propagation and subsequently adjusts its network weights through backpropagation in response to the resulting prediction errors. Through this iterative learning process, BPNN can represent complex nonlinear relationships between manufacturing process parameters and product quality. In this study, BPNN is employed as the primary model to evaluate the capability of a simple neural network on a limited production dataset. The BPNN model was implemented using a learning rate of 0.001, 20 neurons, a batch size of 10, and 50 training epochs, with these settings maintained consistently across all experiments. BPNN was chosen due to its ability to model potentially nonlinear relationships between molding process conditions and the occurrence of product defects. To assess its predictive performance, BPNN was benchmarked against Random Forest (RF) and Support Vector Machine (SVM) using identical datasets and experimental conditions. Each model was tested

across ten independent repetitions, and its performance was assessed based on Accuracy, AUC, Precision, Recall, F1-score, Specificity, and confusion matrices.

Random forest is an ensemble method that constructs numerous decision trees and combines their results. Its advantages include robustness to noise, the ability to capture nonlinear interactions, and interpretability through feature importance. This model is well-suited for tabular data in manufacturing processes [20]. Support vector machine is a supervised learning method that seeks the optimal decision boundary with the maximum margin. With the use of kernels, SVM can map data into higher-dimensional spaces, thereby enabling better separation of nonlinear decision boundaries. This model is frequently employed when the dataset size is limited and classes exhibit overlapping [21].

3. METHODOLOGY

3.1 Data and research variable

The research data originates from the actual production process at a plastic injection molding factory in Taiwan. The dataset comprises 500 records, with 461 non-defective products and 39 defective products. The class ratio of approximately 11:1 indicates the presence of data imbalance that must be addressed prior to model training. The input variables include cycle time, pressure-maintaining switching position, injection end point, melt end point, and melting time. The output variable is the product quality status, classified as either non-defective or defective. Table 1 presents the operational definitions of the research variables used in the study.

Table 1. Research Variable Definition

No	Variabel	Unit	Role
1	Cycle time	second	Initial input
2	Pressure-maintaining switching position	mm	Initial input
3	Injection end point	mm	Initial input
4	Melt end point	mm	Initial and significant input
5	Melting time	second	Initial and significant input
6	Product quality	0 = not defective; 1 = defective	Output

3.2 Research stages

The research methods began with the systematic collection of raw data from production and careful processing such as removal of faulty entries or inconsistencies. After this initial processing, the data collected underwent thorough normalization procedures to ensure all raw variables were properly standardized and positioned on a purely comparable mathematical scale. Then, to comply with the overall split of 80:20 for training/testing, the total data was segmented into separate discrete datasets. In order to resolve class distribution problems, the Synthetic Minority Over-sampling Technique (SMOTE) was only and specifically performed on the training data subset. This focused approach ensured adequate balance of the minority defective class without any risk of leakage or contamination of independent test data. Then the clear regression analysis methodology was presented whose goal was to emphasize and select what parameters had been statistically distinguishable from one another in their contribution to the overall process. Based on this selection process, a total of two important parameters were directly used to construct and fully train three different prediction architectures, including Back Propagation Neural Network (BPNN), Random Forest (RF), and Support Vector Machine (SVM) models. To assess the reliability and robustness of our empirical findings, the predictive performance for each separate machine learning model was evaluated in a highly reliable manner by subjecting it to ten independent experimental repetitions.

Model performance was evaluated based on accuracy, AUC, precision, recall, F1-score, specificity, and confusion matrix. We selected accuracy and AUC as the main criteria for comparison as they provide complementary evaluations of overall performance. Accuracy measures the number of times the model correctly classified a sample. AUC measures the model's ability to distinguish between defective and non-defective items at different classification thresholds. We did not only evaluate accuracy, since the dataset is imbalanced (461 non-defective versus 39 defective). Additional metrics including precision, recall, F1-score, specificity and confusion matrices are used to assess the classification errors and the

ability of the model to identify defected and non-defected items. The whole process of this study is illustrated in Figure 1.

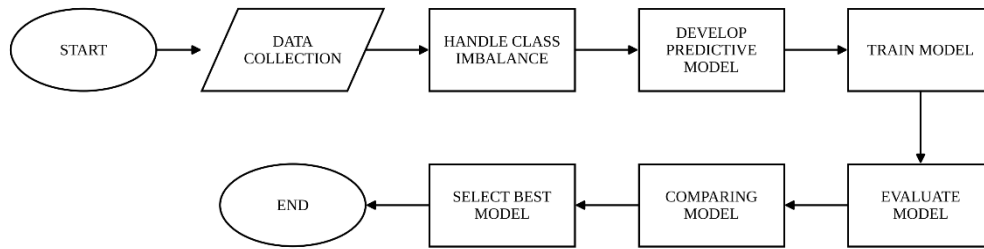


Figure 1. Research methodology

3.3 Parameter and Regression Filter

Regression is purposefully used as an initial screening technique to systematically remove irrelevant or less relevant variables, thus significantly improving the interpretability of the model from a clear analysis perspective. Table 2 presents the regression analysis results for the five process parameters.

Table 2. Results of the regression analysis of process parameters

No	Feature	Cofisien	Std. err	t-value	p-value
1	Cycle time	-0.0401	0.114	-0.351	0.726
2	Pressure-maintaining switching position	-0.1530	0.099	-1.549	0.122
3	Injection end point	-0.1953	0.110	-1.772	0.077
4	Melt end point	-0.2521	0.100	-2.514	0.012*
5	Melting time	0.6511	0.106	6.139	0.000*

Regression analysis was used as an initial feature-screening method to identify process parameters that were significantly associated with product quality. Five process parameters were evaluated. Melt end point had a coefficient of -0.2521 with ($p = 0.012$), while melting time had a coefficient of 0.6511 with ($p < 0.001$). The other three parameters did not reach the ($p < 0.05$) significance level. Therefore, melt end point and melting time were selected as the reduced input variables for subsequent model development. This feature-reduction step was intended to simplify the predictive model while retaining process variables with statistically significant relationships to product quality. The resulting models therefore used two input variables rather than all five initial process parameters.

3.4 Quality Prediction Model

The appropriately developed and systematically configured BPNN model was used with carefully selected optimal parameters specifically such as a learning rate = 0.001, 20 neurons arrangement internally, batch size of 10 for training data processing, and epoch = 50 (computational time). Each model was evaluated by over ten experimental repetitions. Accuracy and AUC were used as the primary metrics for model comparison because they provide complementary information about overall classification correctness and class-discrimination capability. Precision, Recall, F1-score, and the confusion matrix were additionally used to examine the model's defect detection behavior. The results from the ten repetitions were summarized using the median performance for model comparison.

Additionally, the structurally strong RF model was trained on a very large ensemble of 190 individual tree classifiers constrained by maximum depth of 10 with a minimum samples leaf requirement of exactly 1 and minimum samples split threshold equal to two while an explicit max features parameter was set to square root. Following a like manner, the support vector machine (SVM) based predictor was applied within a separate setup including parameter $C = 1000$, as well as specific delta value and coef0 values of scale and 0.3 respectively; meaning a math sigmoid kernel was then used for the same SVM approach. Finally, all three of these advanced computational models were subjected under tightly controlled experimental conditions and standardized testing environments to a rigorously blind head-to-head comparison of their capabilities, to ensure absolute methodological fidelity across the board.

4. RESULT AND DISCUSSION

4.1 BPNN Model Results

After a cautious expansion of the set of first five parameters to extract just two, this general collection performed exceptionally, becoming very efficient regarding the application of the BPNN model. This functionality and performance are achieved with a simple, compact model producing a better classification accuracy between 0.8998–0.9087 and an AUC metric strictly from 0.9408 to 0.9500 over all dates considered. These quantified performance values suggest a potentially very strong dual discriminative power, indicating quite reliably that the analytical framework has an improved ability to distinguish whether an item is defective vs surface clean in product form. Table 3 describes the BPNN result when using the reduced set of input parameters.

Table 3. BPNN Results with Reduced Parameters

Run	Accuracy	AUC
1	0.9014	0.9408
2	0.9055	0.9421
3	0.9016	0.9454
4	0.9041	0.9478
5	0.9087	0.9488
6	0.9063	0.9500
7	0.9046	0.9444
8	0.8998	0.9428
9	0.9003	0.9417
10	0.9081	0.9484

4.2 Random Forest Model Results

Likewise, the random forest algorithm shows a high and stable overall performance applied to a restricted systematic parameter space. The accuracy metric in the analysis estimates specifies appropriate values for this analytic range [0.8811, 0.8871], bounded by min and max; while the AUC takes [0.8825, 0.8895]. However, even these specific quantitative evaluation values are greatly reduced in direct comparison with their corresponding classification results generated by the BPNN, but random forest (RF) model showed a great classification capacity at an adequate level of relative stability during long series experimental repetitions. Table 4 shows the performance of the Random Forest model when using the reduced set of input parameters.

Table 4. RF results with reduced parameters

Run	Accuracy	AUC
1	0.8811	0.8825
2	0.8846	0.8842
3	0.8827	0.8863
4	0.8836	0.8874
5	0.8829	0.8869
6	0.8852	0.8871
7	0.8853	0.8895
8	0.8842	0.8852
9	0.8864	0.8861
10	0.8871	0.8875

4.3 Support Vector Machine Model Results

When fit, the SVM model attained a remarkably stable predictive ability with an overall accuracy metric that intersected solely within a relatively narrow scope (bounded between 0.8811 and 0.8863) coupled with Area Under the Curve (AUC) values anchored tight between 0.8810 and 0.8874 during the evaluation phase of this study; These quantitative empirical results unambiguously demonstrate that SVM methodology has in itself the natural ability to be effectively employed for reliably analyzing and modeling strictly limited production data (however, when applied to the very unique structural specifics of this particular dataset set, its overall predictive performance is somewhat inferior relatively direct AI solutions generated by both Random Forests (RF) and Back Propagation Neural Network (BPNN). This considerable difference in comparative predictive performance is most probably due to some intrinsic properties of the actual process data, given that these very data characteristics can generally be more easily and accurately captured, extracted, and learned through the general neural network architecture providing sophisticated nonlinear feature representations in this domain. Table 5 describes the SVM result when using the reduced set of parameters.

Table 5. SVM results with reduced parameters

Run	Accuracy	AUC
1	0.8842	0.8871
2	0.8863	0.8836
3	0.8827	0.8812
4	0.8812	0.8825
5	0.8852	0.8843
6	0.8843	0.8862
7	0.8821	0.8810
8	0.8836	0.8852
9	0.8834	0.8863
10	0.8811	0.8874

4.4 Model Comparison

Figure 2 and Figure 3 shows the comparison of three machine learning models, which are BPNN, random forest, and SVM using the reduced set of input parameters.

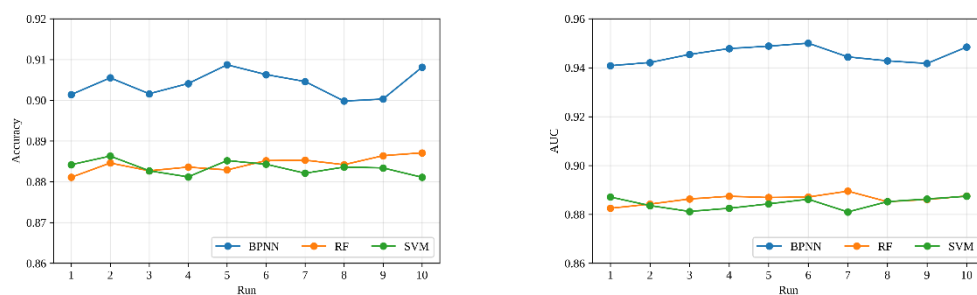


Figure 2. Comparison of Accuracy and AUC of the Reduced Model

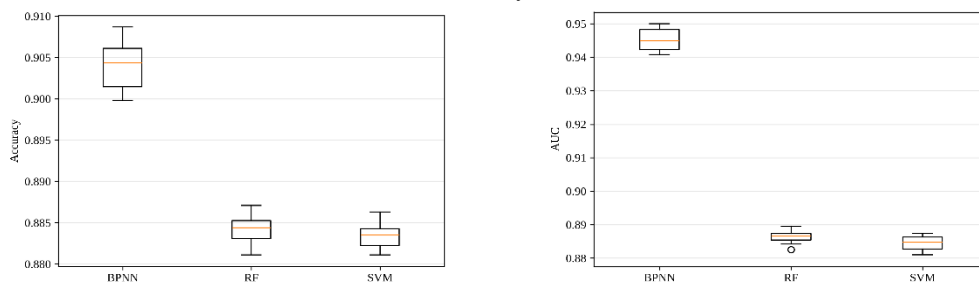


Figure 3. Box plot of model accuracy and AUC

Furthermore, a detailed assessment and then comparison of the predictive models reveal that the BPNN offers best performance indices obtaining for instance accurate median with value 0.9044, also presenting a huge score median AUC equal to 0.9449 seconded by SVM model. Both RF and SVM results are much lower than these top performers, with RF giving a median accuracy of 0.8844 and a median area under ROC curve (AUC) of 0.8873 while the SVM providing similar outputs: median accuracy of 0.8835 and median AUC of 0.8848 respectively. The high efficiency of BPNN is due to its ability to understand the non-linear relations between the selected process parameters, melting point and melting time and product quality through iterative weight modification during back-propagation. While RF and SVM can model non-linear relationships, BPNN appears to have better captured the different patterns in this dataset.

Additionally, ANOVA and its associated analytical results conclusively confirm that statistically significant differences exist between the models examined and are meaningful in both the overall accuracy variable as well as in each AUC assessment. Thus, the BPNN is then selected as the best performing and named as final model for this case of application in quality prediction based on these experimental results and also its evidently favorable statistical attributes. Table 6 shows the comparison between BPNN, random forest, and SVM using three additional classification metrics, while Figure 4 shows exactly how the BPNN model classified the products.

Table 6. Additional evaluation of the deduced model

Model	Precision	Recall	F1-Score	Interpretation
BPNN	0.912	0.904	0.908	Best performance with most balanced defect detection
RF	0.889	0.883	0.886	Stable performance and well-suited for tabular data
SVM	0.887	0.881	0.884	Good performance, slightly lower than RF

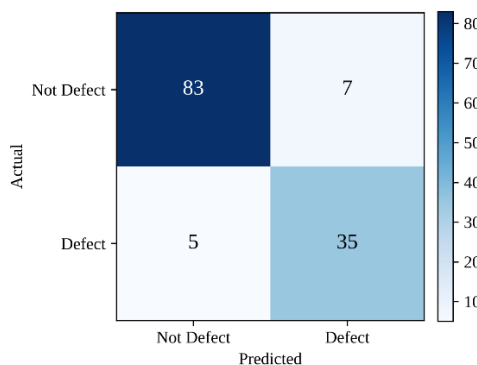


Figure 4. Confusion matrix of the best BPNN model

The confusion matrix indicates that the BPNN successfully classified 83 non-defective products and 35 defective products correctly. There were 7 non-defective products predicted as defective and 5 defective products predicted as non-defective. In the context of quality control, false negatives are more critical because undetected defective products may proceed to the next process or reach the customer. The relatively low number of false negatives suggests that the BPNN is a viable tool for inspection assistance.

Although BPNN demonstrated superior performance compared with RF and SVM, the current study did not include comparisons with other deep learning architectures. Therefore, the observed superiority should be interpreted within the scope of the models evaluated in this study. Comparisons with alternative deep learning architectures represent an important direction for future research to further establish the competitiveness and generalizability of the proposed BPNN approach.

4.5 Discussion of Industry Implications

Because the results are defined and confirmed based upon empirical observations of all possible outputs, this systematic feature reduction procedure does not diminish or dilute the predictive

characteristics of the computational model overall. Rather instead such a process enhances key measures of performance including total prediction accuracy and Area Under Curve (AUC) metrics. This incredibly convincing reasoning gives a solid direction rooted in deep understanding of driving and their statistical counterpart to investigate effective parameter selection, effectively reducing noise and improving model generalization for previously unseen datasets. Furthermore, for industrial settings, where we tend to work much more closely with the operational & practical aspects of factories, selecting just two of these driving parameters gets you orders of magnitudes higher levels of practicality and simplicity with respect to execution on the production floor than an impractical contrived eighty hundred or thousand parameter approach that may not hold any meaningful significance from a functional standpoint relative to achieving your desired outcomes.

Proper determination of the end point of melting combined with precisely acquired total solidification time can serve as unique higher-order parameters when integrating into more complex systems for in-process monitoring. When continuously measured values of these key operational parameters begin to deviate from established and expected normals, the intelligent monitoring system will issue immediate proactive early warning directly to the human operator. Consequently, these predictive alerts in a timely manner facilitate an entire chain of corrective safeguards, adjusting the target melting duration precisely, ensuring continued monitoring of thermal environmental stability, and recalibrating the fundamental manufacturing process, preventing catastrophic product defects from propagating to affect output integrity at any time during fabrication.

The technology itself, the BPNN framework implementation as well as the overall deployment strategies do not require a rollout of old first phase that fully replaces traditional human-led visual inspection protocols immediately after. Another avenue is that when the model is presented, during a lower bleeding-edge version of this highly advanced computational approach, it could potentially be utilized as a sophisticated decision-making support system to evaluate and render an all-encompassing defect risk score for the items being assessed. The human mediator stays in control and retains total oversight over every step of the decision making process while algorithmic model almost serves as a fully complementary tool whose purpose is only to significantly reduce total screening times and systematically curb bias introduced through the human evaluation processes with very high confidence. At this point, as more empirical data piles up and the neural net model is rigorously reaffirmed against physical reality through constant real-world application, the entire technology architecture can be systematically fine tuned with a perspective that spans from long term ambitions of complete automation of inspection modalities or adaptive control techniques.

5. CONCLUSION

This study demonstrated the potential of machine learning for predicting product quality in a plastic injection molding process using actual production data. Regression analysis identified melt end point and melting time as significant process parameters, allowing the predictive models to be developed using a reduced set of inputs. SMOTE was applied only to the training data to address the substantial class imbalance.

Among the evaluated BPNN, RF, and SVM models, BPNN achieved the best overall performance based on the reported Accuracy and AUC results. The additional classification metrics and confusion-matrix analysis provided further insight into its defect-detection capability. These findings suggest that a compact BPNN model using a small number of statistically significant process parameters can serve as a potential decision-support tool for manufacturing quality inspection.

The main contribution of this study is the integration of statistical feature screening, training-only imbalance handling, and comparative evaluation of lightweight machine-learning models using limited real production data. However, the dataset represents a single production environment and a limited number of observations. Therefore, the findings should not be generalized to other products, materials, or manufacturing facilities without further external validation. Future research should evaluate the approach using larger datasets, additional production conditions, and comparisons with other deep-learning architectures.

AUTHOR CONTRIBUTIONS

R.M.S: Conceptualization, Methodology, Writing (original draft). F.A.P: Validation, Writing (review & editing).

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ETHICAL CLEARANCE STATEMENT

This study did not involve human participants, personal data, or animals; ethical clearance was not required.

DECLARATION OF AI TOOL USAGE

The authors declare that no generative AI or AI-assisted technologies were used in the preparation of this manuscript.

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