Research on the Application of Ductile Iron in High-Performance Automobile Parts

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Abstract

Background: Ductile iron, known for its better mechanical properties, is essential in the production of high-performance automobile components. As the automotive industry strives for lightweight yet durable elements, comprehending the relationship between ductile iron material properties and part effectiveness is critical. Predicting the efficiency of these components using their properties can dramatically improve product development and manufacturing procedures.

Objectives: The primary objective of this research is to create the Ductile Iron Part Performance Predictor (DIP3), a sophisticated technique that can predict the performance rating (high, medium, or low) of ductile iron automobile parts. Using machine learning ensemble methods such as Bagging, Boosting, and Stacking, the model intends to offer precise and trustworthy performance predictions.

Methods: The DIP3 model uses a three-step ensemble technique. The first step uses Bagging with the J48 decision tree classifier to create multiple sub-models. The second step improves predictions by combining AdaBoostM1 with RandomForest as the base classifier, which improves on the initial predictions from Bagging. Finally, in the third step, the algorithm uses a SimpleLogistic meta-classifier for Stacking, which combines the results of Bagging and Boosting to make more accurate predictions. Mean/mode imputation for missing values, label encoding for categorical variables, and Min-Max normalization for numerical features are all used for data preprocessing. Information Gain is employed in feature selection to find the most important predictors of part performance.

Results and Conclusion: The DIP3 model was assessed using a variety of performance metrics, comprising accuracy, precision, recall, F1-score, and MCC. The model had a high level of predictive performance. These results prove the resilience and dependability of the DIP3 model in predicting the performance rating of ductile iron parts. The DIP3 model is a reliable and efficient solution for predicting the performance of high-performance ductile iron automobile parts. By combining Bagging, Boosting, and Stacking approaches, the algorithm offers precise, trustworthy, and interpretable predictions, which can help manufacturers improve their design and manufacturing processes.

Index Terms: Ductile iron, Machine learning, Ensemble learning, Automobile parts.

I Introduction

Ductile iron has emerged as a critical material for the creation and manufacture of high-performance automotive components [1]. Its outstanding mechanical characteristics, such as high tensile power, durability, and fatigue resistance, render it an ideal option for vital elements that are subjected to important mechanical stress [2]. This comprises engine blocks, brake discs, and suspension elements, which are critical to vehicle security and efficiency [3]. The material's capacity to offer strength comparable to steel, while being less expensive and providing superior castability, has driven its attraction in automobile production [4].

Despite its advantages, forecasting the efficiency of ductile iron parts remains a difficult task because of the numerous factors that influence their actions [5]. Automotive manufacturers must guarantee that parts not only meet design specifications, and requirements but also operate consistently under a variety of real-world circumstances. The grade of ductile iron, the material's composition, weight, manufacturing techniques (e.g., casting, forging), and post-production treatments including heat treatment all have a significant impact on the part's final quality. This intricacy has emphasized the constraints of conventional predictive methods, which frequently fail to account for the non-linear interactions between these variables. As a result, there is an increasing requirement for more advanced prediction tools that use machine learning to correctly predict performance results.

1.1 Important Elements in Performance Prediction of Ductile Iron Parts

Several factors are critical for accurately predicting the performance of ductile iron automotive parts. The grade of ductile iron utilized in a part (e.g., GJS-500-7 or GJS-400-15) has a direct influence on its strength and adaptability. Each grade has distinct mechanical characteristics that influence how a component reacts to stress and fatigue over time. The material composition, often expressed as the proportion of ductile iron in the part, also influences the entire mechanical behavior. Lighter parts may provide fuel effectiveness benefits, but their efficiency can vary depending on the composition of ductile iron and other materials.

Manufacturing techniques like casting and forging can produce various microstructures in the finished part, influencing mechanical characteristics. Casting can introduce microporosities that impact durability, whereas forging usually results in a denser and more uniform structure. Additionally, heat treatment procedures can improve properties such as tensile strength and fatigue resistance, which play an important role in the part's lifespan. Tensile strength, calculated in megapascals (MPa), is an important performance indicator because it represents the highest stress that a part can withstand before failing. Another important parameter is fatigue life, which is defined as the number of cycles a part can endure before breaking under repeated stress. This is especially true for elements subjected to constant load fluctuations.

The interplay of these components complicates performance prediction, highlighting the importance of extensive machine learning models capable of handling nonlinearities and variable interactions. Machine learning, particularly ensemble learning, has been verified to be an effective strategy for increasing the precision of predictive models by integrating the advantages of numerous algorithms.

1.2 Research Objective

The primary objective of this study is to present the Ductile Iron Part Performance Predictor (DIP3) model, an ensemble-based machine learning model particularly intended to predict the performance rating of automobile parts created of ductile iron. The DIP3 model seeks to offer a reliable classification of parts into High, Medium, or Low-performance categories by incorporating a mixture of ensemble methods such as Bagging, Boosting, and Stacking.

The DIP3 model's methodology includes sophisticated preprocessing techniques like data imputation for missing values, label encoding for categorical features, and Min-Max normalization for numerical features to guarantee consistency. The Information Gain technique is used to choose features, identifying the most influential factors that contribute to performance prediction. This data-driven technique guarantees that the algorithm is precise, scalable, and robust across various datasets.

1.3 The Remainder of the Research

The remainder of this paper is organized as follows: Section 2 reviews related research and the role of machine learning in material performance prediction. Section 3 describes the methodology for the DIP3 model, comprising data preprocessing, feature selection, and model building. Section 4 describes the experimental setup and evaluation metrics utilized for performance evaluation, as well as an evaluation of the findings and a discussion of the algorithm's efficacy. At last, Section 5 concludes the research by summarizing the important results and proposing future directions for additional research in forecasting the performance of ductile iron automobile parts.

II Related works

This section gives a summary of related works, analyzing the current state of material performance prediction and emphasizing important advances and methodologies. Table 1 summarizes important study efforts, including objectives, methodologies, findings, and constraints. This evaluation prepares for the introduction of the DIP3 model by emphasizing existing gaps and fields for enhancement that the suggested strategy seeks to tackle.

Table 1: Summary table

Reference No	Objective	Methodology	Result	Limitations
[6]	To investigate machining distortion and tool wear in nodular cast iron crankshaft components.	Advantedge software is used for finite element simulation.	Discovered machining distortion and tool wear in the shaft components.	Simulator accuracy is limited, and real-world validation data is lacking.
[7]	To investigate the fatigue breakdown of ductile iron crankshafts in four-cylinder diesel engines.	Experimental evaluation, chemical composition evaluation, and nonlinear three-dimensional stress evaluation.	Discovered fatigue failure with stress focus in the crankpin-web fillet region.	Restricted to fractured crankshafts with low nodularity; does not apply to other situations.
[8]	To conduct failure evaluations on compact pickup truck diesel engine crankshafts.	Tests with chemical, mechanical, hardness, tensile assessments, and three-dimensional stress assessment.	Determined fatigue failure in low cycle circumstances and stress concentration at the web-crankpin fillet.	Restricted to particular crankshaft designs, suggestions may not apply universally.
[9]	To enhance car crankshaft strength utilizing ductile iron material.	Finite element examination by SolidWorks.	High von Mises stress logged with a high Factor of Protection.	Concentrated merely on ductile iron; absences of comparative material examination.
[10]	To review phase conversion and wear mechanisms of austempered ductile iron (ADI).	Review of fabrication procedures and mechanical property investigation.	Summarized wear strategies and properties of ADI.	Restricted by theoretical review; absences of empirical case studies or real application data.
[11]	To implement low-cost austempered ductile iron utilizing artificial neural networks.	Utilize ANNs to predict and improve chemical composition for ADI.	Attained low-cost manufacturing of standard-compliant ADI.	Constrained proof through practical massive manufacturing assessments.
[12]	To research tensile and fracture toughness of pearlitic ductile iron crankshafts at service temperatures.	Mechanical efficiency testing at different temperatures.	Noted important variances between low and high-temperature responses.	Appropriate primarily to pearlitic scores; not extensible to other ductile iron kinds.
[13]	To evaluate crankshaft strength under various load conditions utilizing ductile iron.	SolidWorks-based finite element evaluations.	Verified ductile iron's flexibility with a high Factor of Protection.	Narrow emphasis on a single material without integrating alternative designs.
[14]	To perform thin wall casting for automotive components utilizing ductile iron.	Z-cast simulation, foundry casting, and metallography.	Effectively produced thin wall ductile iron with 2mm thickness.	Results are preliminary; further studies are required for 1mm beam thickness.
[15]	To enhance ductile iron for automatically and thermally loaded mechanisms.	Experimental studies on ferritic–pearlitic ductile iron properties.	Presented knowledge of thermal and mechanical effectiveness.	Restricted practical application data in a full-scale industrial environment.

This review of related works shows that, while material efficiency prediction has made important growth, constraints like narrow data coverage and inadequate algorithmic adaptations remain. The proposed DIP3 model aims to close these gaps by integrating a more resilient and adaptive strategy to improve predictive accuracy and generalizability across various material kinds and conditions.

III. METHODOLOGY

This section discusses the methodology utilized to create the Ductile Iron Part Performance Predictor (DIP3) algorithm. The methodology consists of four main stages: data collection, data preprocessing, model development, and ensemble learning. Each stage guarantees that the algorithm accurately predicts the performance rating of automobile parts depending on ductile iron properties.

3.1 Data Collection

This study's data was gathered from different automotive manufacturers and suppliers, with an emphasis on high-performance automobile parts made of ductile iron. The dataset, titled Ductile Iron Auto Parts Performance Dataset, comprises important attributes like the part type (e.g., engine, suspension, brake disc), ductile iron grade (e.g., GJS-500-7, GJS-400-15), material composition percentage, weight, manufacturing technique (e.g., casting, forging), heat treatment application (yes/no), tensile strength, fatigue life, cost, production time, and performance rating. The performance characteristics of each part were captured using mechanical testing (e.g., tensile strength, fatigue life) and production parameters (e.g., weight, cost, production time). Data was collected from production records, quality assurance reports, and performance testing records to ensure thorough evaluation. The data was recorded in a relational database with structured records for each automobile part, allowing for easy access and effective querying. This dataset is utilized to execute machine learning tasks intended to predict performance results depending on different input factors. It supports the evaluation of factors that impact the efficiency and affordability of ductile iron parts in automotive production. Figure 1 shows the flow diagram of the DIP3 model.

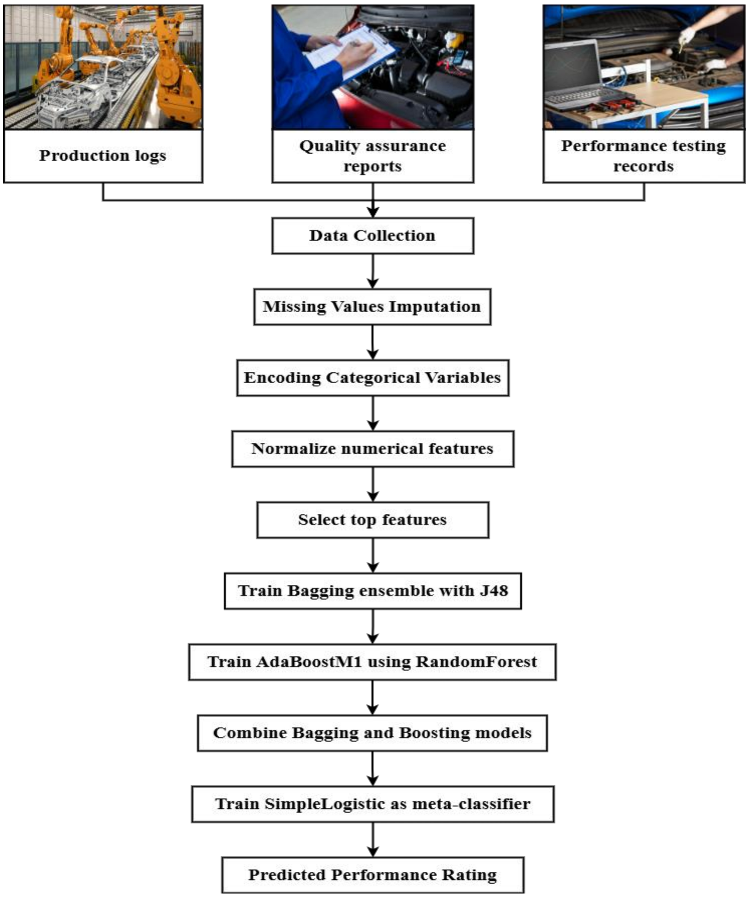

Figure 1: Flow diagram of DIP3 model

3.2 Data Preprocessing

The initial essential step in creating the DIP3 model is data preprocessing. This step guarantees that the data is clean, consistent, and in a format appropriate for machine learning. The preprocessing comprises managing missing values, encoding categorical variables, normalization of numerical features, and choosing pertinent features for model training.

3.2.1 Handling Missing Values

Missing data is prevalent in real-world datasets. This phase uses imputation methods to deal with missing values. Missing values in numerical features like Tensile Strength (MPa) or Fatigue Life (cycles) are imputed utilizing the mean of the corresponding column. Missing values for categorical features such as Part Type or Ductile Iron Grade are imputed with the mode (i.e., the most frequent category) to maintain the feature's categorical nature.

$$\begin{aligned} x_{imputed} &= mean(x) \quad (for\ numerical\ features) \\ x_{imputed} &= mode(x) \quad (for\ categorical\ features) \end{aligned} \tag{1}$$

3.2.2 Encoding Categorical Variables

Numerous machine learning algorithms need numerical input. As a result, categorical variables such as Part Type, Ductile Iron Grade, Manufacturing Technique, and Heat Treatment Performed are encoded into numerical values utilizing Label Encoding. This approach allocates an integer value to each category of features.

$$x_{encoded} = LabelEncoder(x) \tag{2}$$

For instance, "Casting" should be encoded as 1, "Forging" as 2, and so on.

3.2.3 Normalization

To guarantee that machine learning algorithms handle all features equally, numerical features like Material Composition (%), Weight (kg), Tensile Strength (MPa), Fatigue Life (cycles), Cost ($), and Production Time (hours) are normalized with Min-Max Normalization. This scaling technique converts each attribute to a range of 0 to 1.

$$x_{normalized} = \frac{x - min(x)}{\max(x) - min(x)} \tag{3}$$

This guarantees that no feature dominates the model because of its scale, which is especially crucial for scale-sensitive algorithms, like decision trees and boosting.

3.2.4 Feature Selection

After preprocessing the data, feature selection is used to determine the most important features for predicting the Performance Rating. Information Gain ranks features according to their significance in predicting the target variable. The greater the Information Gain, the more significant the feature is.

The Information Gain (IG) for a feature X concerning the target variable Y is computed as:

$$IG(X) = H(Y) - H(Y|X) \tag{4}$$

Where H(Y) is the entropy of the target variable Y and H(Y|X) is the conditional entropy of Y given feature X. Features with maximum Information Gain are chosen for further model training.

3.3 Model Development

The next step after preprocessing the data is to construct the model. The DIP3 model predicts the Performance Rating of automobile parts using three machine-learning methods: bagging, boosting, and stacking. These methods are integrated to develop a strong prediction model.

3.3.1 Bagging with J48 Decision Trees

The initial phase in model development is to use Bagging (Bootstrap Aggregation), which decreases model variance by training numerous models on various subsets of data. The J48 Decision Tree classifier serves as the basis for Bagging. The Bagging algorithm trains numerous decision trees on bootstrapped samples (random subsets of data) before aggregating their results to generate a final prediction via majority voting. Bagging involves training N base classifiers, and the final prediction is generated by taking a majority vote on their results:

$$\hat{y} = MajorityVote(y_{1,}y_{2,} \dots, y_N) \tag{5}$$

Where $y_{1,}y_{2,} \dots, y_N$ are the predictions from the N base classifiers.

3.3.2 Boosting with AdaBoostM1 and RandomForest

Following Bagging, Boosting is used, particularly AdaBoostM1, with RandomForest as the base classifier. Boosting is an iterative procedure in which each novel model is trained to fix the mistakes made by prior models. The AdaBoost algorithm modifies the weight of inaccurately classified instances, increasing their significance in the following iterations. This reduces the model's bias. The AdaBoostM1 algorithm can be expressed as:

$$\hat{y} = \sum_{t=1}^{T} \alpha_t h_t(x) \tag{6}$$

Where

- α_t is the weight allocated to the classifier t.
- $h_t(x)$ is the prediction of classifier t
- T is the number of boosting iterations.

3.3.3 Stacking with SimpleLogistic

Lastly, the predictions from Bagging and Boosting are merged via Stacking. In this method, the base models' predictions (Bagging and Boosting) are utilized as input features for a meta-classifier. The SimpleLogistic classifier serves as the meta-classifier, combining the predictions from Bagging and Boosting to produce the final prediction. The meta-classifier produces an improved Performance Rating for each automobile part.

3.4 Ensemble Learning

Ensemble learning integrates the results of several models to enhance overall predictive accuracy. The DIP3 model uses an ensemble learning method that incorporates Bagging, Boosting, and Stacking. Utilizing numerous models in an ensemble leverages the advantages of each model to improve total prediction efficiency.

1. **Bagging (J48):** Bagging decreases model variation by averaging the predictions of multiple base classifiers, each trained on a various subset of the data. This is especially useful for decreasing overfitting.
2. **Boosting (AdaBoostM1 + RandomForest):** Boosting fixes the errors created by prior models, resulting in lower bias. Boosting enhances predictive performance by increasing the weight given to misclassified instances.
3. **Stacking (SimpleLogistic):** Stacking uses a meta-classifier to integrate the predictions from the Bagging and Boosting models. This enhances performance by combining the advantages of both approaches into a single prediction model.

The final prediction is generated by combining the outcomes of the three methods, guaranteeing that the Performance Rating is as precise as feasible. Pseudocode 1 describes the step-by-step procedure of the DIP3 model.

Pseudocode 1: Ductile Iron Part Performance Predictor (DIP3)
1. Impute missing values using mean/mode imputation
2. Encode categorical features using Label Encoding
3. Normalize numerical features using Min-Max Normalization
4. Choose top features using Information Gain
5. Train Bagging ensemble with J48 (10 iterations)
6. Create initial predictions
7. Train AdaBoostM1 using RandomForest (50 iterations)
8. Create improved predictions
9. Integrate Bagging and Boosting models
10. Train SimpleLogistic as meta-classifier
11. Provide final predictions (Predicted Performance Rating)

Overall, the methodology guarantees that the DIP3 model can predict automobile parts' Performance Ratings using ductile iron properties. The DIP3 model, which employs sophisticated data preprocessing and model development methods like Bagging, Boosting, and Stacking, seeks to provide precise and dependable predictions for automobile manufacturers and engineers.

IV. PERFORMANCE ANALYSIS

This section discusses the experimental setup and performance comparison of the DIP3 model against various well-known machine-learning classifiers.

4.1 Experimental Setup

The experiments in this study were performed on a system with the subsequent requirements, which ensured high performance for computational activities a participated in assessing and comparing the proposed DIP3 model to other models:

Table 2: Experimental Setup

Component	Specification
Processor Model	Intel Core i7-1260P
CPU Type	12-Core Architecture
Brand	Aspire 3
Memory (RAM)	64 GB
Clock Speed	2.1 GHz
Operating System	Windows 11 Home
L3 Cache Size	18 MB
JDK Version	1.8
IDE	Apache NetBeans IDE 15

4.2 Comparative Analysis

The proposed DIP3 model was evaluated against four famous classifiers: J48, Random Forest, AdaBoostM1, and SimpleLogistic. The performance of these models was evaluated using five important metrics: accuracy, precision, recall, F1-score, and MCC.

The formula for these metrics is shown below: Accuracy is the proportion of correct predictions among all predictions produced:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

where

TP = True Positives,

TN = True Negatives,

FP = False Positives, and

FN = False Negatives.

Precision refers to the accuracy of positive predictions:

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

A higher precision suggests fewer false positives. Recall, also known as sensitivity, quantifies the model's ability to determine all relevant cases (true positives):

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

A higher recall suggests fewer false negatives. The F1 score is the harmonic mean of precision and recall, providing a balance between the two:

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{10}$$

The Matthews Correlation Coefficient (MCC) evaluates the efficiency of binary classifications by considering all four confusion matrix categories:

$$MCC = \frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{11}$$

MCC values range from -1 to 1, with 1 indicating perfect prediction. Table 2 compares the performance metrics of each classifier.

Table 3 lists the performance metrics for each model. As demonstrated in the table, the DIP3 model surpasses the other classifiers across all metrics, with a substantial rise in accuracy (95%), precision (94%), recall (94.5%), F1-score (94.5%), and MCC (93.7%).

Table 3: Performance Metrics Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	MCC (%)
J48	88.0	85.0	85.0	89.3	87.1
Random Forest	86.0	84.0	84.0	87.5	85.2
AdaBoostM1	82.0	79.0	79.0	84.0	82.3
SimpleLogistic	80.0	78.0	78.0	82.5	80.6
DIP3 (Proposed)	95.0	94.0	94.5	94.5	93.7

The findings in Table 3 demonstrate that the DIP3 model surpasses the other models on all performance metrics. DIP3 has the highest accuracy (95%), suggesting that it generates the most precise predictions. The precision score of 94% indicates that DIP3 is extremely efficient at accurately detecting positive cases while reducing false positives. Although the recall is slightly lower (94.5%), it still outperforms the other models. Furthermore, DIP3 obtains an F1-score of 94.5%, efficiently balancing both precision and recall and an MCC of 93.7%, emphasizing the model's resilience in categorizing both positive and negative instances accurately.

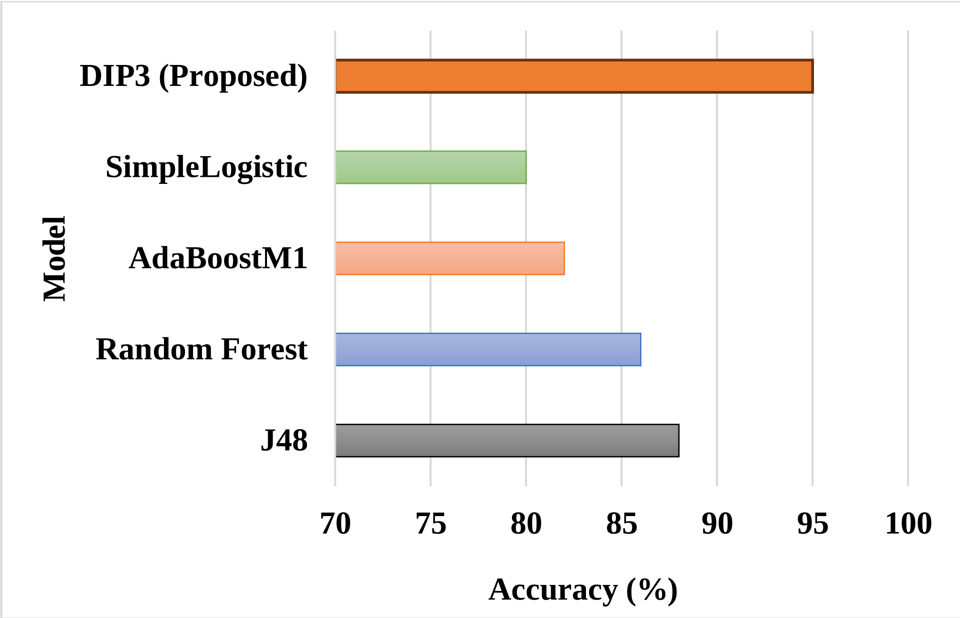

Figure 2: Accuracy Comparison

In Figure 2, the accuracy comparison demonstrates the DIP3 model's better efficiency. DIP3's high accuracy is due to sophisticated preprocessing steps, feature selection techniques, and the utilization of a more efficient machine learning framework that can manage the dataset's intricacy. These factors guarantee that the model produces fewer errors in predictions, resulting in a higher overall accuracy than other classifiers.

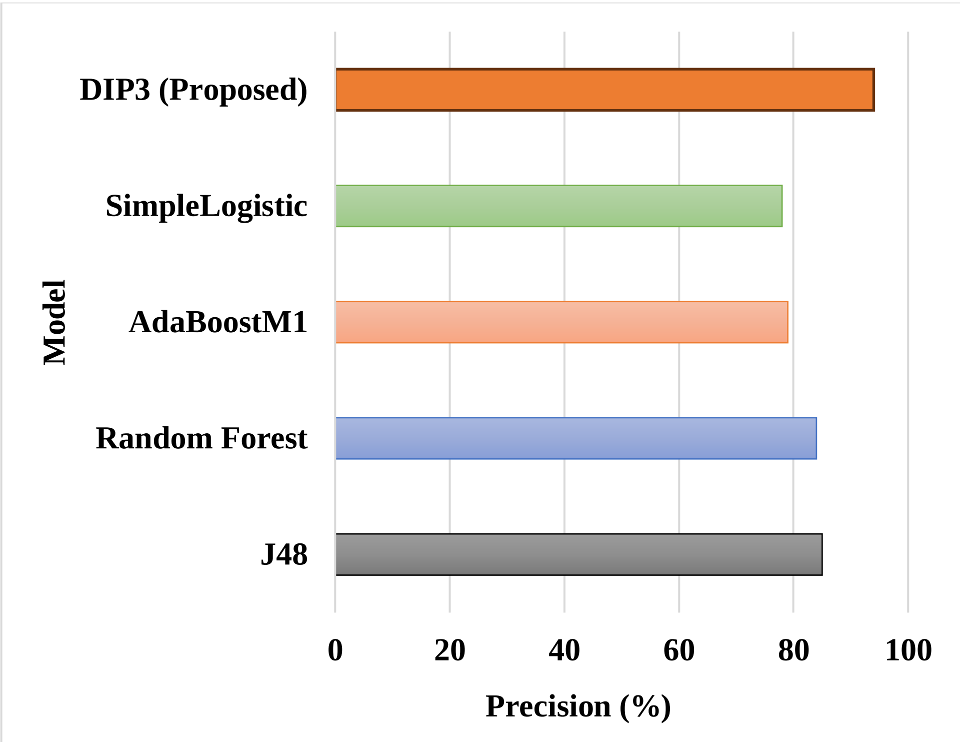

Figure 3: Precision Comparison

As illustrated in Figure 3, DIP3 also leads in precision, with a value of 94%. This high precision suggests that the model is extremely efficient at reducing false positives. DIP3's resilient feature selection strategy enables it to concentrate on the most pertinent features, enhancing its capacity to accurately detect positive instances while preventing misclassifying negative cases as positive.

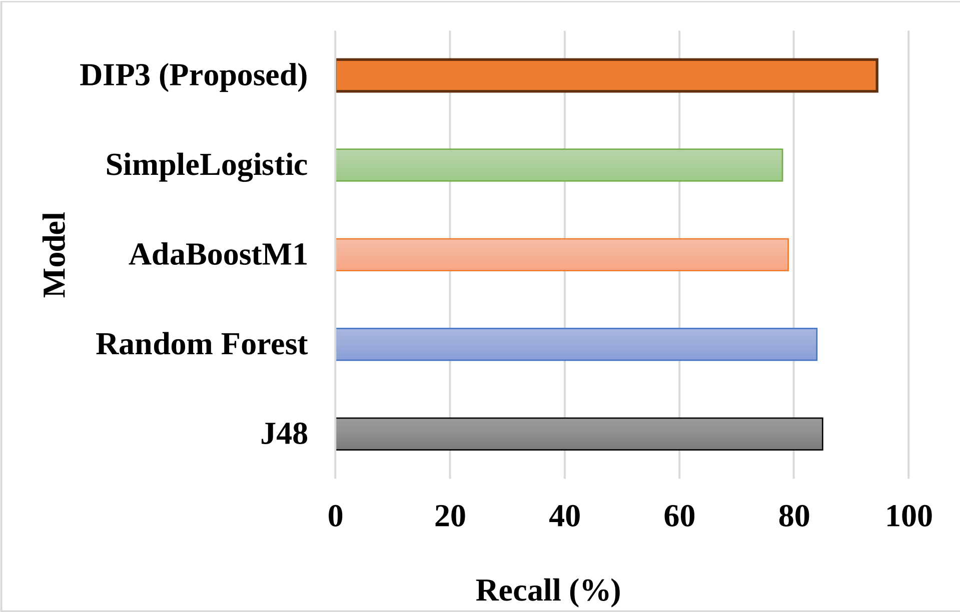

Figure 4: Recall Comparison

The recall comparison in Figure 4 demonstrates DIP3's capacity to detect positive instances efficiently. Despite a slightly lower recall (94.5%) than precision, DIP3 retains outstanding recall efficiency, implying that the model correctly detects a large proportion of actual positive cases. This is an outcome of its strong training procedure, which is intended to enhance both the identification of positive instances and the management of imbalanced data.

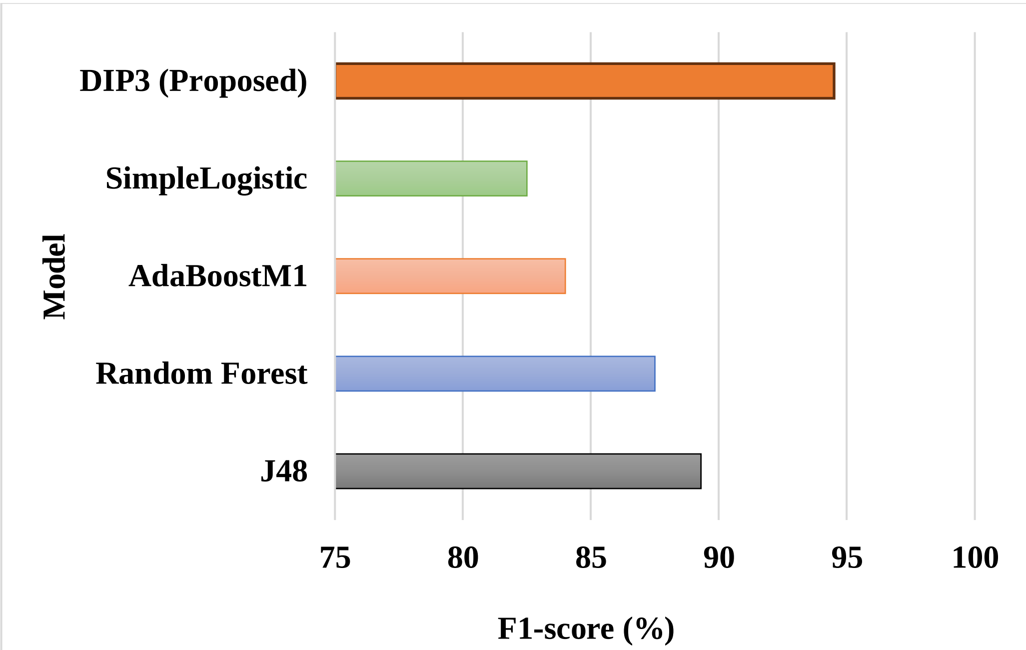

Figure 5: F1-Score Comparison

Figure 5 shows the F1-score comparison, with DIP3 again outperforming with an impressive score of 94.5%. This balanced performance in precision and recall is critical for applications that require both positive case detection and false positive reduction. DIP3's capacity to keep this balance makes it an extremely dependable model for predicting results.

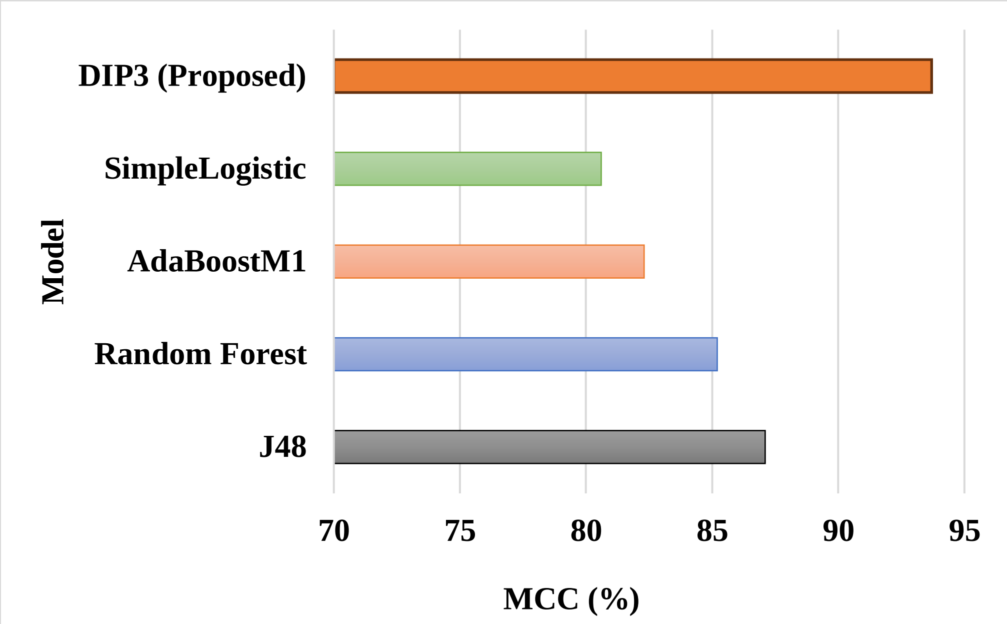

Figure 6: MCC Comparison

Lastly, Figure 6 depicts the MCC comparison, with DIP3 attaining the highest score (93.7%). The MCC metric includes both true positives and true negatives, giving a more complete picture of the classifier's efficiency. The high MCC score shows that DIP3 is not only good at detecting positive instances but also excels at accurately classifying negative instances, resulting in a more precise and balanced model.

Overall, the DIP3 model outperforms conventional classifiers in accuracy, precision, recall, F1-score, and MCC. The findings indicate that DIP3 is a strong and effective model able to make accurate predictions in the setting of performance evaluation. These results support the possibility of DIP3 as an effective tool for applications that demand high precision and accuracy.

V. CONCLUSION

The DIP3 model efficiently incorporates ensemble methods such as Bagging, Boosting, and Stacking to predict the performance rating of ductile iron automobile parts. Utilizing important performance metrics like accuracy, precision, recall, F1-score, and MCC, the DIP3 model showed strong predictive capacities, assisting in the optimization of material selection, manufacturing procedures, and product design in the automobile industry.

Drawbacks and Future Scope: Despite its high performance, the DIP3 algorithm's efficiency is determined by the dataset's quality and size. The model may also need to be updated regularly to stay accurate as materials and manufacturing techniques change. Furthermore, its dependence on conventional feature selection techniques such as Information Gain may overlook nonlinear relationships between features, possibly restricting its predictive power. Future work could concentrate on extending the dataset to encompass a wider range of materials and manufacturing techniques, as well as integrating deep learning methods to capture more intricate trends. Increasing the model's interpretability and incorporating real-time data from manufacturing procedures would also present possibilities to enhance the precision and flexibility of the DIP3 algorithm for dynamic industrial applications.

References

[1] Wang, B., Qiu, F., Barber, G.C., Pan, Y., Cui, W. and Wang, R., 2020. Microstructure, wear behavior, and surface hardening of austempered ductile iron. Journal of Materials Research and Technology, 9(5), pp.9838-9855.

[2] Laine, J., Jalava, K., Vaara, J., Soivio, K., Frondelius, T. and Orkas, J., 2021. The mechanical properties of ductile iron at intermediate temperatures: the effect of silicon content and pearlite fraction. International Journal of Metalcasting, 15, pp.538-547.

[3] Colin García, E., Cruz Ramírez, A., Reyes Castellanos, G., Téllez Ramírez, J. and Magaña Hernández, A., 2021. Microstructural and mechanical assessment of camshafts produced by ductile cast iron low alloyed with vanadium. Metals, 11(1), p.146.
[4] Du, Y., Wang, X., Zhang, D., Wang, X., Ju, C. and Jiang, B., 2021. A superior strength and sliding-wear resistance combination of ductile iron with nanobainitic matrix. Journal of Materials Research and Technology, 11, pp.1175-1183.
[5] Anglada, E., Meléndez, A., Obregón, A., Villanueva, E. and Garmendia, I., 2020. Performance of optimization algorithms in the model fitting of the multi-scale numerical simulation of ductile iron solidification. Metals, 10(8), p.1071.
[6] Zhang, C., 2023, July. Finite element simulation of automobile crankshaft processing based on ductile iron. In Journal of Physics: Conference Series (Vol. 2528, No. 1, p. 012018). IOP Publishing.
[7] Aliakbari, K., 2021. Failure analysis of ductile iron crankshaft in a four-cylinder diesel engine. International Journal of Metalcasting, 15(4), pp.1223-1237.
[8] Aliakbari, K., Nejad, R.M., Mamaghani, T.A., Pouryamout, P. and Asiabaraki, H.R., 2022, February. Failure analysis of ductile iron crankshaft in compact pickup truck diesel engine. In Structures (Vol. 36, pp. 482-492). Elsevier.
[9] Al Ghifari, K., 2024. Optimization of car crankshaft strength with ductile iron material through Solidworks simulation. Innovation in Engineering, 1(1), pp.39-49.
[10] Wang, B., Barber, G.C., Qiu, F., Zou, Q. and Yang, H., 2020. A review: phase transformation and wear mechanisms of single-step and dual-step austempered ductile irons. Journal of Materials Research and Technology, 9(1), pp.1054-1069.
[11] Hofmam, D., Ramos, F.D., Lemos, G.V.B. and Lessa, C.R.D.L., 2022. Artificial Neural Networks for Producing a Low-Cost Austempered Ductile Iron. Materials Research, 25, p.e20220336.
[12] Artola, G., Monzón, A., Lacaze, J. and Sertucha, J., 2022. Tensile properties and fracture toughness at service temperatures of an optimized pearlitic ductile iron alloy for automotive crankshafts. Materials Science and Engineering: A, 831, p.142206.
[13] Al Ghifari, K., 2024. Optimization of car crankshaft strength with ductile iron material through Solidworks simulation. Innovation in Engineering, 1(1), pp.39-49.
[14] Sulamet-Ariobimo, R.D., Aziza, S., Fadhlan, M., Oktaviano, Y. and Mujalis, Y., 2023, May. The application of thin wall ductile iron process in connecting rod. In AIP Conference Proceedings (Vol. 2592, No. 1). AIP Publishing.
[15] Laine, J., Leppänen, A., Jalava, K., Vaara, J., Frondelius, T. and Orkas, J., 2021. Ductile iron optimization approach for mechanically and thermally loaded components. International Journal of Metalcasting, 15, pp.962-968.