Quality Prediction of Resistance Spot Welding with Preheating in Imbalanced Dataset

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***Abstract*—Resistance Spot Welding (RSW) holds significant economic importance across various industries, particularly in the automotive sector, where it plays a crucial role in ensuring the safety and structural integrity of manufactured automobiles. However, when working with galvanized metal sheets, RSW faces unique challenges due to the presence of zinc oxide layer on the surface, which can reduce weld quality. Therefore, a commonly adopted solution is the preheating technique, which helps disrupt this oxide layer and improve weld formation.**

Despite its widespread use, preheating is often overlooked in predictive quality prediction models. In response, this research addresses that gap by investigating the ability of machine learning techniques to classify welding process data between 'good' or 'defective' welds with information from preheating phase. To further improve classification performance—especially in the presence of imbalanced datasets—this study proposes an ensemble-based approach combined with characteristics extraction from physical features of the dynamic resistance curve. An ensemble approach was explored by integrating various base classifiers within a Balanced Bagging Classifier, combined through a Voting Classifier to leverage their complementary strengths. The performance of the ensemble model was rigorously evaluated using cross-validation technique to ensure robustness and generalizability.

The results revealed that the use of balanced bagging classifiers improved the results of classifying defective and good spot welding with respect to default bagging classifiers in the context of imbalaced data.

***Index Terms*—RSW, Imbalance, Preheating, Quality Prediction, Classifier.**

I. Introduction

Resistance spot welding (RSW) is widely used to join components made of metal sheets, such as in the manufacturing of automobiles, trucks, buses, rail vehicles, aircraft structures and space applications [1]. Especially in the automotive industry, more than 90% of welding joinings of a car's body structure are made with RSW, and a modern vehicle typically has between 2,000 and 5,000 weld points [2], ensuring its structural integrity by maintaining cohesion between different components through strong and durable joints.

The Weld quality in RSW is typically defined by the mechanical performance and visual aspects of the weld, as assessed through various measurable attributes. Standard procedures for classification of the weld quality rely on evaluating specific physical indicators, such as fracture mode, tensile or torsional strength, and most commonly, the weld nugget diameter. [6]. These procedures can be either destructive or nondestructive and their goal is to minimize the occurrence of defects such as cold welds, overheated (burnt) welds, and excessive expulsion.

These methods are quite reliable; however, since they are carried out on a sampling basis, they have a significant limitation of being unable to detect defects immediately as they occur. The cost related to parts poorly welded could be very high, as it becomes necessary to follow all the way back though the process the source of the defect, that can be related to the material of the metal parts, machine issues, design problems or even human error. In contrast, online nondestructive evaluation carried out by machine learning techniques applied for evaluation of resistance spot welding present a promising alternative, enabling real-time defect detection for process adjustment and faster reaction time for correction of the problems.

Although this data-driven approach can obtain satisfactory results, three major problems have to be dealt with:

1) Imbalanced data: The proportion between welding data labeled as acceptable weld and defective weld is highly imbalanced, favoring acceptable weld samples.
2) Insufficient data: Some process signals or inspection data can only be collected under specific conditions often requiring expert human intervention, which is time-consuming and expensive, limiting the amount of usable data.
3) Complex welding schedule: Very often it is necessary to define complex welding schedules with preheating phase to address coating-related challenges for weld quality.

The rest of this paper is structured as follows: Section II presents the theoretical background. Section III describes the related works in the literature. Section IV presents the experimental data and the proposed methods. Section V provides the performance evaluation along with a discussion of the results. Finally, Section VI presents the conclusions of this study and outlines directions for future research.

II. Theoretical Background

The RSW process occurs between the contact surfaces of the metal sheets through the heat generated by resistance to the electric current that passes through the parts, between the copper electrodes, subjected to pressure in a small contact area [3].

According to Joule's law, the total heat Q generated during the welding process of a single spot welding is given by (1):

$$Q = \int_0^t R(t) \cdot I^2(t)\, dt, \quad (1)$$

where t_{weld} is the total welding time, $I(t)$ is the instantaneous welding current as a function of time, and $R(t)$ represents the ohmic resistance of the welding zone. This total resistance includes the bulk resistance of the base materials, the contact resistance at the faying interfaces, and the electrode contact resistance.

In the automotive industry, joints involving galvanized steel are common [4]. Due to quality requirements for corrosion resistance, spot welding of zinc-coated steels often necessitates a preheating phase followed by the main welding pulse. The preheating phase promotes controlled melting of the zinc layer, while the main weld ensures adequate nugget formation and mechanical strength [5].

Therefore, by modifying (1) to account for the preheating and main weld phases, the total heat can be expressed as in (2),

$$Q = \int_0^{t_{\text{pre}}} R_{\text{pre}}(t) \cdot I_{\text{pre}}^2(t)\, dt + \int_0^{t_{\text{main}}} R_{\text{main}}(t) \cdot I_{\text{main}}^2(t)\, dt, \quad (2)$$

where t_{pre} and t_{main} are the durations of the preheating and main welding phases, $I_{\text{pre}}(t)$ and $I_{\text{main}}(t)$ are the corresponding time-varying currents, and $R_{\text{pre}}(t)$, $R_{\text{main}}(t)$ are the respective time-dependent ohmic resistances in each phase. Fig. 1 shows the nugget formation accordingly.

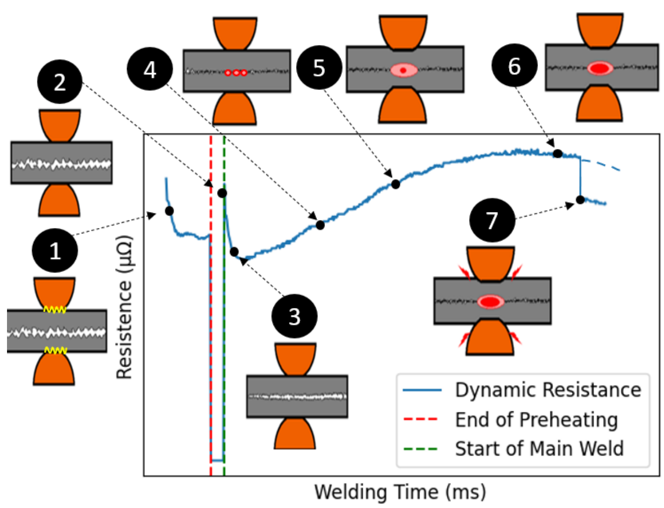

Fig. 1. Weld nugget formation using the preheating technique.

III. Related Works

According to [9], spot weld formation begins in Stage 1, where uneven zinc oxide coatings are removed from the steel surface, enabling better contact. In Stage 2, occur the break down of surface contaminants, resulting in a sharp drop in resistance. During Stage 3, the surface asperities begin to soften and the contact area increases, leading to a further decrease in resistance. Simultaneously, the rising temperature causes an increase in material resistivity.

In Stage 4, the resistivity increase due to the increase of temperature, so it becomes the dominant effect on the resistance curve. The end of this stage typically marks the start of local melting at the asperity contacts. Stage 5 likely begins near the inflection point of the resistance curve, indicating the transition to nugget formation. In Stage 6, continued growth of the molten nugget and mechanical collapse cause the resistance to decrease further. Finally, in Stage 7, if the nugget becomes too large to be contained by the surrounding solid metal under electrode pressure, expulsion occurs.

A. Machine Learning for RSW Quality Prediction

Various machine learning methods have been proposed to monitor spot weld quality and detect process nonconformities. Below is a list of commonly investigated signals, categorized by the nature of the measured attributes from the RSW process, adapted from [7]:

- **Welding Force:** An Artificial Neural Network (ANN) and a convolutional neural network (CNN), respectively, were trained on experimental data to detect expulsions and predict the weld quality metrics (i.e., nugget diameter, nugget thickness, heat affected area (HAZ) diameter, and indentation depth) in [16]. The multi-layer perceptron (MLP) achieved 14.1% relative error on nugget diameter prediction, 15.9% on nugget thickness, 5.4% on HAZ diameter, and 1.6% on indentation depth; the CNN reached 13.6% relative error on nugget diameter prediction, 14.9% on nugget thickness, 7.9% on HAZ diameter, and 1.8% on indentation depth.
- **Acoustic Emission:** A data-based model was built in [18] and then applied on acoustic emission signals for detection of cracks in spot welding that proved to be very useful in identifying damaged spots.
- **Infrared Light Emission:** The use of an infrared (IR) camera for enabling in situ nondestructive evaluation (NDE) of the weld nugget by predicting nugget thickness and diameter is investigated by [19] that uses spatial-temporal instances that are then fed into a conventional CNN, achieving maximum Mean Squared Error (MSE) of 0.57.
- **Electrode Displacement:** An ANN has been built in [17] to use some features extracted from the electrode displacement signals to predict the contact area and thus indirectly the electrode degradation. The model has shown a good accuracy, with a mean error of the contact area about 1.61 and with a standard deviation of about 3.73.
- **Electrical attributes:** The welding voltage curve as input for predictive welding models was solely investigated by [10], which employed an ANN to estimate nugget diameters, achieving a maximum average forecast error of

0.15 mm. The welding current, meanwhile, is often used in combination with other process signals, as demonstrated in [11], where both welding current and voltage were utilized to predict tensile shear strength, nugget size, and fracture mode. The model achieved a high coefficient of determination (R^2) of 0.9978 for nugget size prediction. Notably, the dynamic resistance is among the most commonly used process signals for evaluating and controlling weld quality, as it can indirectly describe variations in the internal characteristics of the base metal sheets and provide significant data to assess the quality of spot welding [8]. Moreover, using the dynamic resistance is considered one of the most suitable for industrial applications. A key concept in utilizing this process signal for predictive modeling is feature extraction in which raw signal data must be transformed into a compact and informative representation that preserves relevant patterns while reducing dimensionality. Techniques such as the popular geometrical attributes approach, Principal Component Analysis (PCA), Autoencoders, and even image-based transformations are employed to convert these signals into features suitable for machine learning algorithms. An ANN algorithm using geometrical featuring extraction was used in [12] to predict the nugget diameter with 90% of predictions within 10% of deviation error. Autoencoder (AE) was used in [13] and was able to capture patterns from the dynamic resistance curve, feeding a Gaussian Process Regression (GPR) model to predict nugget diameter. The AE-GPR framework achieved a RMSE value 0.15 on test data. In [14], a Hopfield neural network, a form of recurrent neural network (RNN), was employed to classify weld quality based on a strength criterion that distinguishes between good and poor welds transforming the dynamic resistance curve into two-dimensional vectors, which are then classified into multiple categories using predefined prototype pattern vectors. In [15], the Mahalanobis Genetic Algorithm (MGA) was implemented using feature selection to address the issue of class imbalance applying the Synthetic Minority Oversampling Technique (SMOTE), demonstrating the effectiveness of the approach in imbalanced settings. The combination of MGA and SMOTE achieved a high classification performance, with an area under the Receiver Operating Characteristic curve (AUC) of 0.91. In the study conducted in [20], after dimensionality reduction by principal component analysis (PCA), an ensemble learning model has obtained as result the (R^2) of 0.75 for nugget size. Another PCA analisys was conducted in [21] combined with an ANN to simultaneously predict the nugget size and failure load. The weld quality was then classified into levels according to the failure load magnitude. Reference [22] proposed a resistance spot welding quality online detection method with dynamic current and resistance data based on a combined convolutional neural network (CNN), long short-term memory network (LSTM), and an attention mechanism that achieved a quality detection accuracy of 98.5%. Another prediction and classification algorithm for welding defects based on the improved generative adversarial network (GAN) algorithm in collaboration with a CNN is proposed by [23] obtaining an overall accuracy of more than 90%. In [24], a one-dimensional convolutional neural network (1DCNN) with channel attention mechanism was developed with accuracy over 96% for multi-class welding quality prediction. In [25], a quality monitoring approach based on isolation forest (iForest) was proposed to identify abnormal welds and normal welds, with an AUC of 0.95.

Therefore, it can be seen from the literature that various types of machine learning models have been used with dynamic resistance curves as input for quality prediction, and many of them are particularly concerned with the challenges posed by small and/or imbalanced datasets.

Table I summarizes the use of various machine learning models applied to dynamic resistance curves, highlighting their corresponding techniques and dataset challenges.

TABLE I
MACHINE LEARNING MODELS WITH DYNAMIC RESISTANCE CURVE

Ref.	*Machine Learning Model*	*Main Technique*
[20]	PCA + Ensemble Models	Dimensionality reduction[a]
[21]	PCA + ANN	Dimensionality reduction[a]
[22]	CNN + LSTM	Signal-to-image transformation
[23]	CNN + LSTM	Attention mechanism[b]
[24]	GAN + CNN	Attention mechanism
[25]	iForest	Anomaly detection[b]
[15]	MGA	Feature extraction[a, b]
[12]	ANN	Feature extraction[a]
[13]	GPR	Autoencoders
[14]	RNN	Pattern recognition

[a] Applied in Small Dataset.
[b] Applied in class-Imbalanced Dataset.

Notably, none of the reviewed studies have considered dynamic resistance curves incorporating a preheating phase. This represents a key contribution of the present research, which not only includes the preheating stage in the analysis but also integrates techniques specifically designed to handle class-imbalanced and small datasets, that is very likely to occur in real world.

IV. EXPERIMENTAL DESIGN AND METHODS

The execution stage was divided in 3 parts:

1) Data Collection: The data were collected from a production line at an automobile factory in Brazil. The input data, represented by process curves and singular features were collected from files generated by the welding machines with the .rui extension, which organize the information in .xml format. The labels were obtained from reports from non-destructive quality testing using ultrasound equipment.

2) Data Preparation: This stage was dedicated to cleaning, transforming, preprocessing the input data, and normalizing and encoding the output labels. Figure 2 illustrates the entire data flow, from the formation of the weld nugget to the model classification regarding weld quality. The dataset obtained at the end of data preparation consists of 441 instances.

Table II presents the distribution of the two classes used in this study. Class 0 corresponds to good spot welds, while Class 1 represents defective spot welds. As shown, the dataset is imbalanced, with a significantly higher number of good welds compared to defective ones in both the training set (329 vs. 23) and the test set (81 vs. 8). This class imbalance is a critical factor to consider during model training and evaluation, as it may affect the performance and generalization of the machine learning models, especially in correctly identifying the minority class (defective welds).

TABLE II
CLASS DISTRIBUTION IN TRAINING AND TEST SETS

Set	Class 0	Class 1
Training	329	23
Test	81	8

3) Feature Extraction Model Construction: As highlighted in the related literature, none of the reviewed studies employing dynamic resistance curves as inputs for machine learning models incorporated the preheating phase in the model development process. Therefore, for the construction of our algorithm, a combination of three techniques was used:

a) Extraction of geometrical features from the Dynamic Resistance Curve (for the main welding phase),

b) extraction of statistical features (for the preheating phase),

c) and the use of Balanced Bagging Ensemble Classifiers approach.

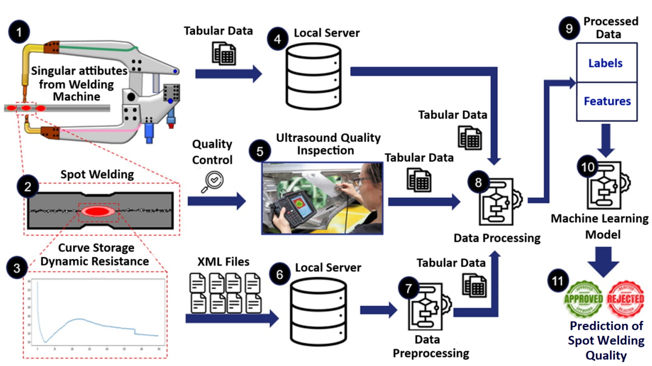

Fig. 2. Data flow: From weld nugget formation to automatic classification.

A. Extraction of geometrical features

For the main welding phase, the technique of extracting critical features from the dynamic resistance curve was adopted, based on the proposal by [27]. The selected points include the first resistance peak (R_a, T_a), the resistance valley (R_b, T_b), the second resistance peak (R_c, T_c), and the final resistance point (R_d, T_d).

From the key points from the dynamic resistance curve, three categories of derived features were calculated: the time variations ΔT_1, ΔT_2, and ΔT_3 (3)–(5); the resistance variations ΔR_1, ΔR_2, and ΔR_3 (6)–(8); and the average rates of resistance change K_1, K_2, and K_3 (9)–(11).

a) The time variation in each stage:

$$\Delta T_1 = T_b - T_a \tag{3}$$

$$\Delta T_2 = T_c - T_b \tag{4}$$

$$\Delta T_3 = T_d - T_c \tag{5}$$

b) The resistance variation in each stage:

$$\Delta R_1 = R_b - R_a \tag{6}$$

$$\Delta R_2 = R_c - R_b \tag{7}$$

$$\Delta R_3 = R_d - R_c \tag{8}$$

c) The average rate of change in each stage:

$$K_1 = \frac{\Delta R_1}{\Delta T_1} \tag{9}$$

$$K_2 = \frac{\Delta R_2}{\Delta T_2} \tag{10}$$

$$K_3 = \frac{\Delta R_3}{\Delta T_3} \tag{11}$$

B. Extraction of statistical features

The extracted statistical features from the preheating phase included: first, second, and third quartiles, skewness, kurtosis, and root mean square. Figure 3 illustrates the entire features used in our work.

Incorporating the preheating phase into predictive quality models is crucial, as this initial segment of the resistance dynamic curve often reflects early material responses and system behaviors that precede the main process.

By capturing and analyzing these early-stage features, models can achieve improved sensitivity and robustness, enabling more accurate predictions and earlier detection of potential deviations in quality.

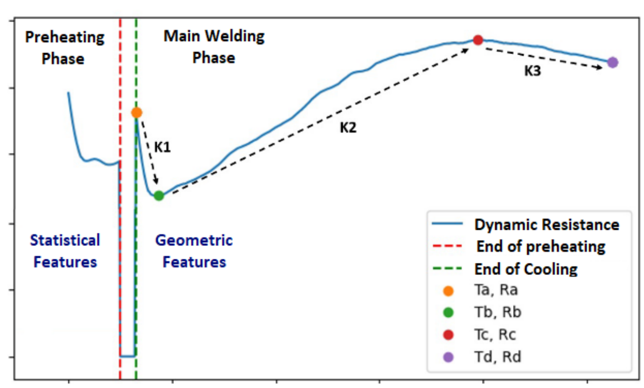

Fig. 3. Critical attributes from the main welding phase and the preheating phase.

C. Balanced Bagging classifiers

Real-world data frequently presents us with imbalanced datasets, where the number of instances in one or more classes is significantly lower than in others. This is the case of the dataset studied in this work, in which the quantity of good welds outnumbers by far the quantity of defective welds. The total number of defective spot welds from the whole dataset was 31 whereas the total number of good spot welds was 410. This imbalance can pose a substantial challenge, as traditional machine learning models often exhibit a strong bias towards the majority class, leading to poor performance on the minority class – the very class that might be of critical interest [26]. To tackle the challenges posed by imbalanced datasets, Balanced Bagging—a variation of the traditional Bagging ensemble technique—is widely used. While standard Bagging reduces model variance by training multiple base learners on random subsets of the training data and aggregating their predictions (typically via majority voting or averaging), Balanced Bagging modifies this approach to account for class imbalance.

The aggregation of base learners' predictions takes into account the characteristics that make each individual learner effective [28]. The combined performance achieved through voting mechanisms helps to improve the model, because the voting process leverages the diversity and complementary strengths of different models. Even if individual classifiers are weak or biased, their collective decision can be more accurate and robust.

Another important technique used winthin this work was the cross-validation, that is a technique used to evaluate the performance of a machine learning model by splitting the training data into multiple subsets (called "folds"). This helps ensure that the model generalizes well to unseen data and is not overfitting.

The key importance of the Balanced Bagging strategy lies in the bootstrapping process. Instead of sampling indiscriminately from the entire dataset, Balanced Bagging ensures that each subset used to train a base estimator has a more balanced class distribution. This is typically achieved through:

- Undersampling the majority class: A random subset of majority class instances is selected, usually matching the size of the minority class.
- Oversampling the minority class: All or most of the minority class instances are included in each training subset.

V. PERFOMANCE EVALUATION

The chosen metric for evaluation was the Balanced Accuracy that is used to evaluate classification models on imbalanced datasets. It is defined as the average of the recall obtained for each class, giving equal importance to both the majority and minority classes. This makes it a more reliable performance measure than overall accuracy when class distributions are skewed. For binary classification, as it is computed in (12):

$$\text{Balanced Accuracy} = \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right) \quad (12)$$

where:

- **TP** = True Positives (defective welds correctly classified)
- **FN** = False Negatives (defective welds misclassified as good)
- **TN** = True Negatives (good welds correctly classified)
- **FP** = False Positives (good welds misclassified as defective)

A. Choosing the Bagging Strategy

The inicial setup focuses on applying and evaluating two ensemble classification methods: the Standard Bagging Classifier and the Balanced Bagging Classifier.

Both classifiers were instantiated with identical random states to ensure reproducibility, using default parameters—specifically, ensembles of 150 decision trees. A key distinction lies in the Balanced Bagging Classifier, which includes a sampling strategy parameter set to 'auto'. This enables automatic under-sampling of the majority class for each base learner (decision trees), helping the model better capture the characteristics of the minority class, even in an imbalanced dataset. After training both models on the same prepared dataset, predictions were generated on the test set.

The Bagging Classifier achieved a balanced accuracy of 0.50 and a geometric mean of 0.00. In contrast, the Balanced Bagging Classifier demonstrated superior performance, with a balanced accuracy of 0.86 and a geometric mean of 0.86, indicating a better ability to handle class imbalance.

Additionally, Table III and Table IV show the confusion matrices to detail the number of true positives, true negatives, false positives, and false negatives, highlighting the impact of the balancing strategy on classification outcomes. It can be seen that the balanced bagging classifier is far superior than the default bagging classifier.

TABLE III
CONFUSION MATRIX – BAGGING CLASSIFIER

Actual \ Predicted	**Class 0**	**Class 1**	**Total**
Class 0	81	0	81
Class 1	8	0	8
Total	89	0	89

TABLE IV
CONFUSION MATRIX – BALANCED BAGGING CLASSIFIER

Actual \ Predicted	**Class 0**	**Class 1**	**Total**
Class 0	69	12	81
Class 1	1	7	8
Total	70	19	89

B. Tuning the number or estimators

Now that we testified the superiority of the Balanced Bagging Classifier, we evaluated the impact of the number of estimators, using the same type of estimator used in the previous setup, i.e., the decision tree.

This analysis systematically varied the number of estimators parameter from 10 to 200 and measured the corresponding balanced accuracy on a held-out test set, allowing for the identification of the values that yielded the best performance for the metric.

Visualizing these scores against the number of estimators in the Figure 4 we can check that when the number of estimators parameter reaches 50, essentially there is no improvement in the balanced acuracy score.

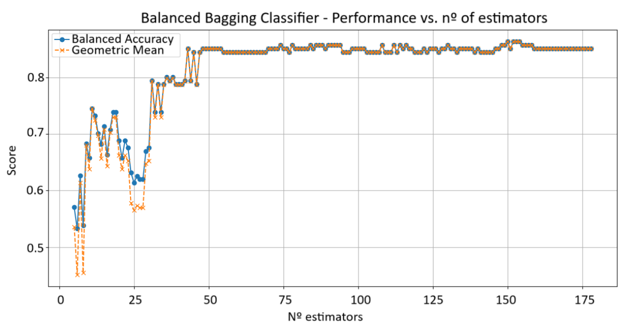

Fig. 4. Evaluation metrics x Number of Estimators.

C. Tuning the sample strategy

By the evaluation of different sampling approaches, we aim to identify if it could optimize model performance. For this purpose, it has been done iterations through a predefined set of sampling strategies.

This parameter defines how the class distribution is balanced for each base estimator. The available strategies are:

- **auto**: Automatically balances class distribution in each bag.
- **majority**: Undersamples only the majority class(es).
- **not minority**: Resamples all classes except the minority.
- **not majority**: Resamples all classes except the majority.
- **all**: Resamples all classes, typically involving undersampling of majority and oversampling of minority classes.

It can be seen in the Figure 5 that only the not majority strategy show poor performance.

D. Tuning the maximum number of features

This section details the process of optimizing the hyperparameter named maximum number of features in our Balanced Bagging Classifier model. This hyperparameter controls the fraction of features considered when training each individual base estimator (decision tree for our study) within the ensemble.

Throughout the screening process, the hyperparameter values where varied in 10 values within the range [0, 1]. It can

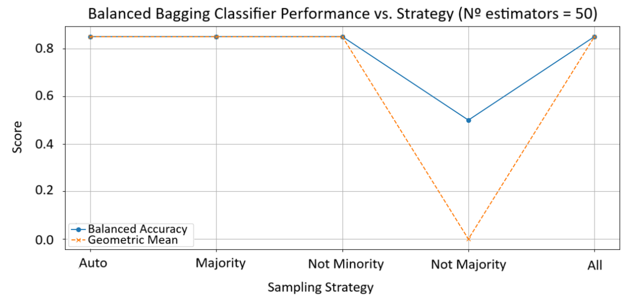

Fig. 5. Evaluation metrics x strategy for resampling the training data.

be seen in the Figure 6 that only using 100% of the features leads to maximum performance.

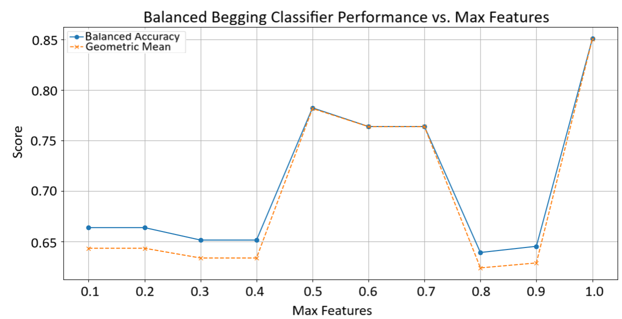

Fig. 6. Evaluation metrics x maximum number of features.

E. Tuning the type of estimator

This section details the experimental methodology employed to evaluate the performance of various base classifiers when integrated within a Balanced Bagging Classifier.

A diverse set of base classifier types was selected for evaluation. This set included:

- **Decision Tree Classifier**: A simple and interpretable model. A fixed maximum depth was applied (`max_depth=15`).
- **Support Vector Classifier (`SVC`)**: A powerful model for complex classification tasks. Due to its sensitivity to feature scaling, the SVC was integrated into a `Pipeline` object with a `StandardScaler`. Hyperparameter tuning for the SVC (`C`, `gamma`, `kernel`, and `degree` for the 'poly' kernel) was performed using `RandomizedSearchCV` with a 3-fold cross-validation on the training data, optimized for `precision`. The best performing scaled and tuned SVC pipeline (`best_scaled_svc`) was then used as a base estimator.
- **Logistic Regression**: A linear model utilizing L1 regularization (`penalty=l1`, `solver=liblinear`).
- **Random Forest Classifier**: An ensemble method known for its robustness. An instance with 100 estimators was used.

- **Gradient Boosting Classifier**: Another powerful ensemble method. An instance with 100 estimators and a learning rate of 0.1 was used.
- **K-Nearest Neighbors Classifier**: A non-parametric, instance-based learner. An instance with 5 neighbors was used.
- **Gaussian Naive Bayes**: A probabilistic classifier based on Bayes' theorem.

The Figure 7 shows that the Gaussian Naive Bayes was the best performing with a balanced accuracy of 0.87 followed by the Decision Tree Classifier with 0.85 and Gradient Boosting Classifier with 0.84. The SVC scored as the worst model with 0.60 for the balanced accuracy.

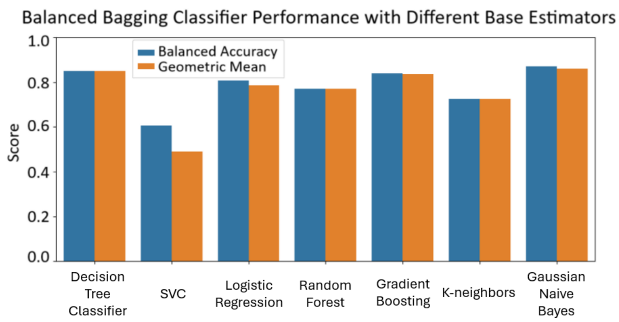

Fig. 7. Comparison between estimators of the Balanced Bagging.

VI. CONCLUSION

A comprehensive and systematic strategy was adopted in this study to investigate the bagging ensemble method for classifying spot welds according to their quality—either good or defective. Firstly, an evaluation metric suitable for imbalanced data was chosen, in place of the commonly used overall accuracy, to ensure a more reliable assessment of model performance. Then, it was concluded that the Balanced Bagging is much more suited for imbalanced real world data from dynamic resistance curves than the defaut bagging. The hyperparameters that gave the best results were the number of estimators starting from the minimum value of 50, and using 100% of features for training the model maximized the balanced accuracy. The type of the estimators also presented better results for the Gaussian Naive Bayes Classifier, but very closely followed by the Decision Tree Classifier and Gradient Boosting Classifier.

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