# Intelligent Manufacturing: Using Intelligent Technologies To Transform Industry

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This paper presents a feature-based paradigm for intelligent manufacturing, highlighting the operational influence of critical variables temperature, operating mode, power consumption, network latency, production speed, and error rate on system efficiency. Four hybrid models were created by integrating Stacking Classification (SC) and Gaussian Process Classification (GPC) with Artificial Rabbit Optimization (ARO) and Coronavirus Herd Immunity Optimizer (CHIO) to elucidate intricate feature connections and improve prediction accuracy. The models—STCO, STAO, GPCO, and GPAO were evaluated using metrics such as Accuracy, F1-score, and Matthews Correlation Coefficient. STAO attained the greatest test accuracy (0.981) and MCC (0.972), thereby validating its exceptional performance. Feature importance analysis indicated that production speed and error rate are the most significant variables. SHAP and FAST studies provided additional insights, indicating that interaction effects among characteristics predominantly influence model behavior. The findings indicate that hybrid intelligent models utilizing feature-level input priority provide enhanced predicted accuracy and increased explainability, rendering them appropriate for real-time industrial application.

**Keywords:** Intelligent Manufacturing; Feature Importance Analysis; Production Efficiency Prediction; Feature-Based Modeling; Bio-inspired Optimization



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## 1. Introduction

Intelligent manufacturing is a paradigm shift in industry, combining advanced technologies with traditional methods to produce more responsive, adaptable, and efficient systems [1]. The underlying principle is interweaving procedures, systems, and devices to support enhanced decision-making, streamlining operations, and dynamic response to ever-changing demands [2]. The transition from conventional manufacturing to adaptive and smart systems has been a response to modern industry dynamics, especially in responding aptly to intensifying production complexity and demands for customization and timely response [3].

Intelligent manufacturing systems rely on a continuous stream of data from a variety of sources, including machines, human operators, digital platforms, and sensors [4]. These systems leverage the data by systematically collecting, analyzing, and processing it to make proactive adjustments to orders and minimize downtime as much as possible [5]. As a result, production lines are less dependent on human intervention. The significant reduction in errors leads to increased production and maximized industry output [6].

Unlike traditional systems, intelligent manufacturing offers built-in flexibility, allowing for dynamic adaptation to shifting demand and reduced waste [7–10].

One fundamental element in bringing intelligent manufacturing to life is interconnectedness. Connected communication systems enable isolated machines and systems to share data and communicate with one another at different manufacturing points [11]. This interconnectivity provides a better overview of the overall manufacturing process and enables operators to observe points of bottlenecking, optimize operations, and achieve overall efficiency [12]. In addition, instant monitoring and feedback loops make continuous development possible and make it easier to maintain consistent product quality [13].

The role of automation in intelligent manufacturing goes beyond the physical aspects. While robot systems perform repetitive or dangerous tasks, digital automation optimizes processes and monitors quality and maintenance programming [14]. Judgment-based decision processes are now complemented by processes capable of analyzing patterns and suggesting action [15]. Rather than replacing human functions, such processes complement strengths and permit releasing staff to perform more high-end strategic functions [16].

Energy efficiency and sustainability are also essential issues for today's manufacturing. Smarter technologies facilitate more sustainable operations by providing optimized energy consumption, less wastage of materials, and enabling better resource management [17]. By balancing operational effectiveness with environmental considerations, manufacturers reduce expenditures while enhancing corporate social responsibility and compliance with regulations [18].

One of the core features of intelligent manufacturing is learning from past and existing data to guide actions in the future [19]. Production history records, maintenance reports, and real-time production data are analyzed to reveal underlying patterns, forecast the failure of equipment or machinery, or determine quality concerns [20]. Over time, systems learn and become better at predicting requirements and more efficient in taking corrective action [21]. The data-led process promotes resilience and aids in ongoing innovation [22].

While it has many benefits, the integration of intelligent manufacturing systems is fraught with challenges [23]. These include harmonization of legacy systems and advanced technologies, data protection issues, high volume and variety data management, and building a workforce with skills to handle and maintain complicated systems [24]. Solving all these challenges involves investing in technologies and achieving a change in the organizational culture towards more collaborative, adaptive, and innovation-encouraging practices [25].

Ultimately, the success of smart manufacturing depends on how good a system is at understanding and reacting to the data it receives [1, 2]. In the case of this work, the goal is to examine how different input variables affect the performance of manufacturing systems and to examine the features of the variables. Quantifying the relative importance of each feature leads to an understanding of the intrinsic dynamics between system performance and input conditions.

### 1.1. Related work

Wang and et.al [26] centered on the contribution of Big Data Analytics (BDA) to the development of intelligent manufacturing systems. It analyzed the way that the explosion of data triggered by the Internet of Things (IoT), 5G, and cloud computing redefined the product design, manufacturing, and process of maintaining products. The paper offered extensive coverage of significant themes, including the definition of big data, model-driven and data-driven paradigms, the structure, development, and applications of BDA, core technologies, the prevailing challenges, and opportunities for further research [3, 4]. The research sought to stimulate novel directions toward the implementation of BDA in intelligent manufacturing. Shojae Inasab et al. [27] investigated the state of the art of Manufacturing Execution Systems (MES) within the framework of Industry 4.0 through a systematic literature survey. It analyzed recent studies and implementations to learn about emerging topics with high potential for future research. The authors applied bibliometric and network analysis to identify influential contributors in the form of impactful institutions, authors, and geographies. The authors identified trend-setting and innovative software technologies that could define the next generation of MES solutions and examined associated surveys to learn about research gaps and limitations. Yang et al. [28] investigated a novel intelligent model for the process industry based on the proposition of a deep coupling of the Industrial Internet and industrial artificial intelligence. It examined the process industry's traditional three-tier framework made up of enterprise resource planning, manufacturing execution systems, and process control systems, and analyzed the process enterprises' modes of decision-making, control, and operation. From this analysis, the study established a framework for intelligent manufacturing and proposed a vision for an intelligent decision-making system assisted by human-machine cooperation, complemented by an autonomous control system. It also established the major scientific issues and technologies required for the implementation of intelligent manufacturing in the process industry to succeed.

Although prior research has examined machine learning applications in intelligent manufacturing, the majority of studies emphasize model performance above the significance of operational variables. There is a paucity of research focusing on feature-level analysis integrated with explainable, optimal classification models for real-time industrial settings. This research addresses the deficiency by introducing an innovative hybrid framework that amalgamates feature significance, stacking classification, probabilistic modeling, and bio-inspired optimization. The contributions comprise (1) a feature-driven modeling methodology, (2) the creation of four hybrid models, and (3) a transparent performance assessment utilizing SHAP and FAST to inform process enhancements.

### 1.2. Objective and Novelty

In contrast to conventional research, which has primarily focused on model-centric enhancements, this project proposes a feature-oriented framework to evaluate and configure intelligent systems for manufacturing. While prior studies have largely aimed to improve classification accuracy using individual machine learning models, this research will specifically investigate how input features—such as temperature, operation mode, power consumption, network latency, production speed, and error rate—impact production efficiency. To achieve this, the project will employ a hybrid modeling strategy that combines Stacking Classification and Gaussian Process Classification, alongside high-performance bio-inspired optimizers such as Artificial Rabbit Optimization (ARO) and the Coronavirus Herd Immunity Optimizer (CO). This approach aims not only to enhance forecasting accuracy but also to uncover latent correlations between operational variables and system responses. The research distinguishes itself by quantifying the relative importance of individual features and assessing the influence of varying operational conditions on system efficiency. This will support targeted process improvements and help reduce the "black box" nature commonly associated with complex machine learning models. Furthermore, the proposed hybrid frameworks (STCO, STAO, GPCO, GPAO) will offer adaptive and explainable decision-making capabilities in dynamic industrial environments. Ultimately, the findings of this study are expected to contribute significantly to both academia and industry by enabling more intelligent real-time monitoring, efficient resource management, and reduced system faults. This research addresses a critical gap in the literature by shifting from model-focused estimation to actionable, feature-level insights that can drive tangible improvements in intelligent manufacturing systems.

The research commences with the procurement of a publicly accessible intelligent manufacturing dataset, succeeded by preprocessing and the determination of six essential operational features. Statistical analysis and p-value filtering ascertain feature importance. The exploration of feature interaction is conducted utilizing FAST and SHAP methodologies. Two base classifiers, Stacking Classification (SC) and Gaussian Process Classification (GPC), are combined with two bio-inspired optimizers, ARO and CHIO, yielding four hybrid models (STCO, STAO, GPCO, GPAO). These models are assessed utilizing parameters including accuracy, precision, recall, Matthews correlation coefficient (MCC), and area under the curve (AUC). A comparative study is performed among models and classes, yielding insights into feature impact and model resilience in intelligent manufacturing.

## 2. Study methodology

### 2.1. Data Collection

The data provided for this study was gathered from a publicly accessible dataset, the "Intelligent Manufacturing Dataset" (available at https://www.kaggle.com/datasets/ziya07/intelligent-manufacturing-dataset). Synthesized but realistic records simulated the conditions of a smart manufacturing environment. The data are representative of different operational parameters gathered for different production conditions and are utilized to measure, predict, or estimate system efficiency. Only a subset of the features most appropriate to operational efficiency and performance was utilized for this research.

Operation_Mode is the current state of the manufacturing system. It is a categorical variable that is usually in the range of 0 (off/idle), 1 (partial operation), to 2 (normal operation). Temperature, measured in degrees Celsius inside the manufacturing environment, can affect equipment performance and power usage. Power_Consumption, the system's real-time power consumption in kilowatts, delivers information about the system's efficiency and the operational load. Network_Latency, the delay in communication in milliseconds across devices networked in the manufacturing system, is applicable to real-time data exchange and control. Production_Speed is the number of units produced per hour, which immediately indicates the system's productivity or throughput. Error_Rate, the proportion of process failures or malfunctioning units to total output, is an important measure of the quality of the produced items. Efficiency_Status, a classification label for the efficiency of the system as a whole, typically a 0 (low), 1 (medium), or 2 (high).

Table 1 presents the statistical properties of various input and output variables within an industrial production system. Among the input variables, Temperature ranges from 30.013 to 89.999, with a mean of 60.063 and a standard deviation of 17.362, indicating moderate variability. Power_Consumption and Network_Latency have mean values of 5.739 kW and 25.462 ms, respectively, both exhibiting relatively high dispersion. Production_Speed stands out as the most variable input, with a wide range (50.287 to 499.981) and a high standard deviation of 121.683, reflecting significant operational fluctuations. The Error_Rate averages 4.206%, suggesting occasional inaccuracies during operation. As the output variable, Efficiency_Status ranges from 0 to 2, with a mean of 1, indicating average performance across the dataset. Based on the data, Production_Speed appears to be the most influential and variable input factor, exerting the greatest impact on both system efficiency and operational stability.

Fig. 1 shows the p-values of different input features in a radar chart of a feature selection method, where p-values less than 0.05, including zero, indicate the selection of a feature as significant. Four features qualify in the chart: Temperature (0.00161), power consumption (0.04962), production speed (0), and Error_Rate (0). These are checked with a green box, indicating their significance to the model. The overall average p-value of all features is 0.337, indicating most features are insignificant with weaker significance. Features such as Quality_Control_Defect_Rate (0.89244) and Predictive_Maintenance_Score (0.8012) are statistically weakly associated, as shown by the high p-values. The radial layout facilitates visually evaluating the significance levels, where proximity to the center represents greater statistical relevance. Generally, the chart highlights that a subset of the variables contributes significantly to the prediction or modeling process and streamlines more efficient and interpretable model building.

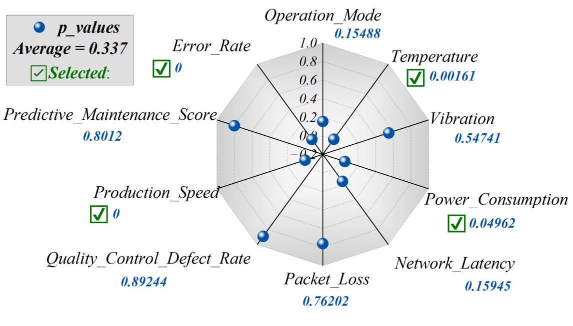


**Fig. 1.** Feature selection for the input variables.

### 2.2. Stacking Classification (SC)

Stacking or stacked generalization is an ensemble learning methodology used to enhance predictive performance by aggregating multiple classifiers [29]. Rather than trusting a single algorithm, stacking involves a two-stage hierarchical structure. The first stage includes a set of base learners like decision trees, support vector machines, or k-nearest neighbors, all trained independently on a common dataset. These base models produce predictions as the input to a second-stage model, the meta-classifier or blender. The meta-classifier is trained to learn how to combine the base models' predictions best to achieve the desired output [30]. This framework helps capture varied decision patterns and overcome the shortcomings of each model by providing a better generalization to unseen data.

### 2.3. Gaussian Process Classification (GPC)

This describes the theory of Gaussian Process Classification (GPC) for the case of binary classification [31]. In this case, the aim is to predict a binary label of 0 or 1 for a given input example based on a learned model. GPC adds a latent function f, which describes the underlying input-output relation and is parameterized as a Gaussian Process (GP). A GP is a probabilistic model with a mean function and a covariance kernel so that the function values at any finite list of inputs have a joint Gaussian distribution. For classification, the latent function. However, Akon f(x) specifies the probability of the label according to a Bernoulli distribution with the probability of class 1 provided by the cumulative Gaussian distribution function evaluated at Humanity Alban f(x). Under the given dataset of input-output pairs, the class labels are considered conditionally independent in case the latent function is known. Therefore, the likelihood can be factorized over all instances. However, since the likelihood for GPC is not Gaussian, the posterior over the latent function cannot be written in closed form. To overcome this, approximate techniques are employed, namely, the Expectation Propagation algorithm. EP approximates the posterior with a Gaussian distribution by iteratively matching moments of the marginal posteriors. After approximating the posterior, the predictive distribution for a novel case is still Gaussian. From the latter, the model estimates the probability that the novel label is 1. The last classification is done by choosing the label with the largest predicted probability. This procedure produces the so-called Optimal Bayesian Classifier (OBC), which is the classifier that has minimal expected classification error under the model assumptions [32]. GPC thus offers a probabilistically consistent and flexible framework for classification based on the characteristics of the Gaussian Processes.

**Table 1.** Statistical properties for the variables.

| Distribution | Category | Variable | Indicator | | | |
|---|---|---|---|---|---|---|
| | | | Max. | Min. | Avg. | St. Dev. |
| Normal | Input | Operation | 0 | 2 | 0.397 | 0.661 |
| | | Temperature_C | 30.013 | 89.999 | 60.063 | 17.362 |
| | | Power_Consumption_kW | 1.500 | 9.999 | 5.739 | 2.443 |
| | | Network_Latency_ms | 1.000 | 49.998 | 25.462 | 14.147 |
| | | Production_Speed_per_hr | 50.287 | 499.981 | 345.989 | 121.683 |
| | | Error_Rate_% | 0.000 | 14.992 | 4.206 | 4.116 |
| | Output | Efficiency | 0 | 2 | 1 | 0.817 |

### 2.4. Artificial Rabbit Optimization (ARO)

The ARO algorithm is motivated by the natural rabbit foraging and hiding behaviors in the wild [33]. The rabbits tend to avoid alerting others to their burrows by eating more distantly from them. They also construct several burrows for escape as well as protection, which allows them to escape predators by using quick, random movement and opportunistic hiding. These defensive behaviors provide the basis of the ARO algorithm's construction as they mimic the behaviors mathematically and computationally optimized to solve optimization problems. In ARO, candidate solutions are all represented as rabbits within the search space. The process starts with an initialization step when rabbit positions are dispersed randomly throughout the problem's dimensional space. Two primary tactics drive the search: detour foraging (exploration) and random hiding (exploitation). In detour foraging, the rabbits alter their positions by social interactions with one another that imitate their natural behavior of foraging for food but not taking the most straightforward paths. It keeps the diversity of the search space high and increases the odds of avoiding local optima. For exploitation, the strategy of random hiding is used. Each rabbit creates several potential hiding positions (burrows) around its current location and selects one of them randomly as its new location, with the introduction of stochastic variation and decreasing search radius as the iterations go on. This makes the system more convergent and yet flexible. All along the way, rabbits adjust their positions by evaluating the fitness of their original and proposed positions and keeping the better ones. An energy shrink function is used to control the smooth transition between the exploration and exploitation phases by mimicking the dissipation of energy. Essentially, the ARO algorithm translates elegant biological behaviors into alternative computational methods in a novel way, providing an efficient, flexible optimization process that is generally usable for complex problems [34].

### 2.5. Coronavirus herd immunity Optimizer (CO)

In this paper, the CHIO algorithm is presented as a means of improving the classification performance of the AdaBoost machine learning classifier by optimizing its parameters more effectively [35]. The real-life pandemic control methods of social distancing and the concept of herd immunity are the inspiration behind the CHIO algorithm. These social and biological phenomena are formulated as the basis of the machine learning classification improvement principles in reducing complexity and augmenting precision. CHIO separates the population into three categories: contaminated (infected), vulnerable (susceptible), and immune. It starts by initializing population individuals and optimization parameters, and each is represented as a set of genes within certain boundaries. The fitness of an individual represents their immunity level or solution quality. An individual population (also referred to as Herd Immunity Population or HIP) is created, and status is randomly allocated to each member as infected or susceptible. The algorithm's backbone is a process of iterative development with gene updates based on interactions mimicking disease transmission and recovery under social distancing conditions. These updates are contingent on a number generated randomly and the individual's status of health, using other infected, susceptible, or immune individuals as guides for the gene changes. As the iterations go on, the population is updated according to individuals' improved fitness. If there is no improvement of an infected individual within a certain number of iterations (specified by MaxAge), the individual is deemed dead and replaced by a new random individual. This ensures diversity and prevents the population from getting trapped in local optima. The process of optimization goes on until the stopping condition is reached, generally, the number of iterations. At the end of it all, the population should ideally be dominated by immune (fit) individuals that signify an optimized set of solutions. This innovative method combines epidemiological dynamics with computational optimization to enhance the performance of the classifier effectively [36].

### 2.6. Performance Evaluation Metrics

An outline of the evaluation criteria used to assess the models' accuracy and correlation is provided in this section, along with a methodical approach to hybrid model implementation. The assessment metrics are defined by the following mathematical formulas:

Accuracy is defined as the proportion of actual results examined across all cases. Precision is the proportion of correctly predicted positive observations to all predicted positive observations. Recall is the True Positive Rate, also known as Sensitivity, which is the proportion of correctly predicted positive observations to all real class observations. The Matthews Correlation Coefficient (MCC) value, which runs from -1 to 1, is a reliable metric for assessing the effectiveness of classification models that take into account all values of TP, TN, FP, and FN.

$$\text{Accuracy} = \frac{(TP + TN)}{(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN})} \tag{1}$$

$$\text{Precision} = \frac{TP}{(\mathrm{TP} + \mathrm{FP})} \tag{2}$$

$$\text{Recall} = \frac{TP}{(\mathrm{TP} + \mathrm{FN})} \tag{3}$$

$$\text{MCC} = \frac{((FP \times FN)) - (TP \times TN)}{\sqrt{(TN + FN)(TN + FP)(TP + FN)(TP + FP)}} \tag{4}$$

TP (True Positives) denotes accurately predicted positive instances, FP (False Positives) signifies erroneous positive predictions, TN (True Negatives) refers to accurately predicted negative instances, and FN (False Negatives) implies overlooked positive instances. These variables constitute the foundation for computing accuracy, precision, recall, F1-score, and MCC in the assessment of model performance.

Because of their proven ability to handle high-dimensional, nonlinear optimization problems which are consistent with the complexity of intelligent industrial systems ARO and CHIO were chosen. Both techniques are excellent for optimizing hybrid classification models because of their quick convergence and great exploration–exploitation balance. CHIO's diversity-preserving population dynamics and ARO's foraging-inspired search mechanism perform better than many conventional optimizers at avoiding local optima. Their inclusion over more traditional methods like Genetic Algorithms or Particle Swarm Optimization is justified by comparative studies in recent literature that demonstrate their higher performance in industrial and classification tasks.

## 3. Result and discussion

In the case of intelligent manufacturing, system performance needs to be measured against parameters of operation to achieve reliability, quality, and efficiency. The research in this case revolves around the examination of the influence of six factors operation mode, temperature in degrees Celsius, power consumption in kW, latency in the network in milliseconds, rate of production in units per hour, and error percentage on the system efficiency overall, which is implied through the label for the performance status. Two fundamental classification models, STC and GPC, were utilized to capture the intricate, nonlinear interactions among these variables and enhance the accuracy of the predictions. To also enhance the model performance, two nature-inspired optimizers, ARO and CHOI, were implemented within the learning process. These combinations produced four hybrid models: STCO, STAO, GPCO, and GPAO. The performances of these models have been assessed based on a wide range of performance measures, comprising Accuracy, Precision, Recall, F1-score, and MCC. These measures offer a strong and well-balanced estimation of the classifiers based on the various facets of their performance. Synthesizing feature-based analysis with hybrid intelligent modeling, the research provides an integrated perspective on how the conditions of operation influence manufacturing efficiency, enabling more data-driven and intelligent choices in smart production systems.

A comparative performance evaluation of different developed models under training and testing scenarios is shown in Table 2 on intelligent manufacturing. The models STOCKC, STCO, STAO, GPC, GPCO, and GPAO are compared based on common classification metrics: Accuracy, Precision, Recall, F1-score, and MCC, providing insights into their prediction quality and generalization capacity. Within the models, STAO is consistently better than others at both the training and testing stages. STAO has the best test accuracy of 0.980, with a perfect match in Precision, Recall, and F1-score at 0.980 and a maximum MCC of 0.972, showing high performance and low overfitting. This demonstrates that STAO is reliable when it comes to precise real-world industrial classification applications. GPAO also presents high results with a test accuracy of 0.973 and an MCC of 0.959, closely following STAO. GPCO also excels in its baseline version, GPC, on all counts and demonstrates the efficacy of the optimization layer in improving model performance. Although STCO also outperforms STOCKC, the difference is less, and its ultimate performance is lower than GPAO and STAO. Interestingly, GPC, as a good base model, falls short on both the training and test stages by obtaining a test accuracy of merely 0.931 and an MCC of

0.897. This demonstrates the significance of hybridization and fine-tuning in achieving stable model performance.

The findings highlight the importance of optimization in smart manufacturing systems. Hybrid and optimized models such as STAO and GPAO exhibit better precision and stability, which is essential to reducing downtime and enhancing process quality. MCC values confirm such models to have balanced performance even in class-imbalanced scenarios. The findings support the necessity of advanced hybrid approaches in industrial AI systems to guarantee precision and robustness in real-time decision-making.

Good classification between different operating states is necessary for quality control, predictive maintenance, and making decisions in smart manufacturing. Table 3 presents a detailed performance assessment of six developed models over three target classes: High, Low, and Medium. These classes probably represent different system performance or risk levels and have to be correctly discriminated against using multi-class discrimination. STAO also outperforms across all classes. In the High class, it shows the best precision (0.959), recall (0.982), and F1-score (0.970), suggesting outstanding identification of high-performance or hazardous states. Likewise, even in the low-class, representing system failure or degradation states, STAO has an F1-score of 0.980 and MCC of 0.970, establishing confidence in sensitive identification tasks. For the Medium class, usually the most uncertain and subject to misclassification, STAO again excels with perfect precision of 1, recall of 0.981, and F1-score of 0.990, verifying its consistency across the board. GPAO is also suitable, with all scores closely following STAO; thus, it is a good substitute. GPC and STOCKC models do relatively poorly with relatively low MCC and F1-scores, indicating poorer overall classification stability and a higher probability of misclassifying borderline or noisy examples. These results support the necessity of strong hybrid modeling in smart manufacturing, particularly in complicated multi-class tasks. The consistently high performance of STAO and GPAO in all three classes shows their ability to serve real-time decision systems needing both accuracy and flexibility. The high MCC values also guarantee their robustness against class skewing and qualify them as good tools to deal with dynamic manufacturing environments. In Fig. 2, the confusion matrices provide an overall comparison of the performance of the models in three target classes: high, medium, and low. Through the matrices, it is possible to gain insights into the strengths and weaknesses of each model by observing both correct predictions (diagonal values) and misclassifications (off-diagonal values). Starting with GPC, while it makes a high number of correct predictions for the "High" class (2798), it does poorly with "Medium" and "Low" classes, misclassifying 229 and 245 as "High", respectively, and reflecting heavy confusion between the two classes. There is an appreciable improvement by GPCO with higher correct classification in all three classes, with particular emphasis on "Low" with as many as 2863 correct and fewer misclassifications between "High" and "Medium". GPAO improves further and records as many as 2895 correct predictions both in "Medium" and "Low" with little confusion: 91 errors in both classes and 95 misclassifications from "High" to "Low". Moving on to the second group of models, STOCKC shows fair performance but still has considerable misclassification rates, e.g., 170 "Medium" and 182 "Low" values misclassified as "High" that indicate minimal ability to differentiate between closely abutting classes. STCO does better by strongly improving on correct "High" class predictions to 2893 and on reducing cross-class errors between "Low" and "Medium". STAO has the best balanced and precise performance among all six models, with nearly flawless classification: 2932 "High", 2919 "Low", and 2928 "Medium", with minimal off-diagonal errors. In total, the comparative study unequivocally shows a marked increase in the quality of classification from base models (GPC and STOCKC) to their optimized or hybrid versions (GPAO and STAO). GPAO and STAO are the best-performing and most robust models and exhibit a strong ability to generalize and little confusion among classes, whereas GPC and STOCKC exhibit a high misclassification rate and weaker performance. This trend indicates the importance of optimization in enhancing classification accuracy by all target classes.

The charts in Fig. 3 illustrate ROC curves indicating how models differ when it comes to correctly identifying positives (true positive rate) and falsely identifying negatives as positives (false positive rate). Each model shows the area under the curve (AUC), which is the most important measure of exactitude. In the first image, the STOCKC model has an AUC of 0.958 and outperforms the GPC model with an AUC of 0.945 as well, and the STOCKC curve is noticeably closer to the top-left corner of the graph, reflecting more accurate classes. In the second image, STCO achieves an AUC of 0.974 and marginally outclasses GPCO with an AUC of 0.965; in addition to this, the difference is even more pronounced at low FPR values. In the third image, STAO has the best AUC of 0.985, and a close second follows with GPAO having an AUC of 0.977.

Furthermore, the STAO curve closely follows the perfect top-left corner, indicating extremely good classification capabilities. In practical applications, particularly in smart manufacturing, the applicability of such high-performance

**Table 2.** Results of the developed models based on the two considered phases.

| Evaluators | Model | | | | | |
|---|---|---|---|---|---|---|
| | STOCKC | STCO | STAO | GPC | GPCO | GPAO |
| Train | | | | | | |
| Accuracy | 0.942 | 0.965 | 0.980 | 0.925 | 0.952 | 0.968 |
| Precision | 0.945 | 0.966 | 0.980 | 0.929 | 0.954 | 0.969 |
| Recall | 0.942 | 0.965 | 0.980 | 0.925 | 0.952 | 0.968 |
| F1-score | 0.943 | 0.965 | 0.980 | 0.926 | 0.953 | 0.968 |
| MCC | 0.914 | 0.947 | 0.970 | 0.889 | 0.929 | 0.952 |
| Test | | | | | | |
| Accuracy | 0.951 | 0.970 | 0.981 | 0.931 | 0.956 | 0.973 |
| Precision | 0.952 | 0.971 | 0.981 | 0.934 | 0.957 | 0.973 |
| Recall | 0.951 | 0.970 | 0.981 | 0.931 | 0.956 | 0.973 |
| F1-score | 0.951 | 0.971 | 0.981 | 0.932 | 0.956 | 0.973 |
| MCC | 0.927 | 0.956 | 0.972 | 0.897 | 0.934 | 0.959 |

**Table 3.** Results of the developed models based on three classes.

| Evaluators | Model | | | | | |
|---|---|---|---|---|---|---|
| | STOCKC | STCO | STAO | GPC | GPCO | GPAO |
| High | | | | | | |
| Precision | 0.890 | 0.931 | 0.959 | 0.855 | 0.912 | 0.941 |
| Recall | 0.950 | 0.969 | 0.982 | 0.937 | 0.951 | 0.968 |
| F1-score | 0.919 | 0.950 | 0.970 | 0.894 | 0.931 | 0.954 |
| MCC | 0.877 | 0.924 | 0.955 | 0.840 | 0.896 | 0.931 |
| Low | | | | | | |
| Precision | 0.950 | 0.969 | 0.982 | 0.936 | 0.951 | 0.968 |
| Recall | 0.939 | 0.965 | 0.978 | 0.918 | 0.959 | 0.970 |
| F1-score | 0.944 | 0.967 | 0.980 | 0.927 | 0.955 | 0.969 |
| MCC | 0.917 | 0.950 | 0.970 | 0.891 | 0.933 | 0.953 |
| Medium | | | | | | |
| Precision | 1 | 1 | 1 | 1 | 1 | 1 |
| Recall | 0.943 | 0.964 | 0.981 | 0.923 | 0.949 | 0.970 |
| F1-score | 0.971 | 0.982 | 0.990 | 0.960 | 0.974 | 0.985 |
| MCC | 0.958 | 0.973 | 0.985 | 0.943 | 0.962 | 0.977 |

models has a far-reaching influence because they are capable of identifying faults early and efficiently, thus avoiding sudden failures by implication, production processes are less interrupted, and product quality shifts to a higher plane. In turn, the integration of models like STAO into automated decision-making and control systems is a milestone toward greater efficiency and achieving smart and future-proofed factories. The bar graph below in Fig. 4 shows the output of a FAST (Fourier Amplitude Sensitivity Test) sensitivity analysis that calculates the impact of input parameters on the model output. Two indices are shown: S1 (first-order index) in green, indicating the direct effect, and ST (total order index) in purple, indicating the direct and interaction effects. The graph shows S1 values are extremely low across all variables (between 0.004 and 0.007), while ST values are remarkably high (between 0.856 and 0.873). This shows that none of the input variables individually has a strong effect, but their interactions and combinations contribute a significant amount to the output. Specifically, temperature, error rate, and production speed have the maximum ST values, revealing their significance through interactive effects with other variables. The considerable gap between S1 and ST indicates the sensitivity of the model to nonlinear dependencies and variable interactions. Overall, direct effects are negligible, but interactions are essential to system performance. In manufacturing systems with intelligence, responses are a result of multiple features interacting simultaneously instead of a single-factor effect. Under such circumstances, numerical analysis must be grounded on comprehending such multifarious multivariate behavior. Temperature, error rate, and production speed features should be evaluated interactively, not independently. Identification of such latent patterns lies at the core of smart decision-making, predictive maintenance, and process efficiency optimization in manufacturing with intelligence.

The suggested hybrid models, specifically STAO and GPAO, provide significant practical applicability by facil-

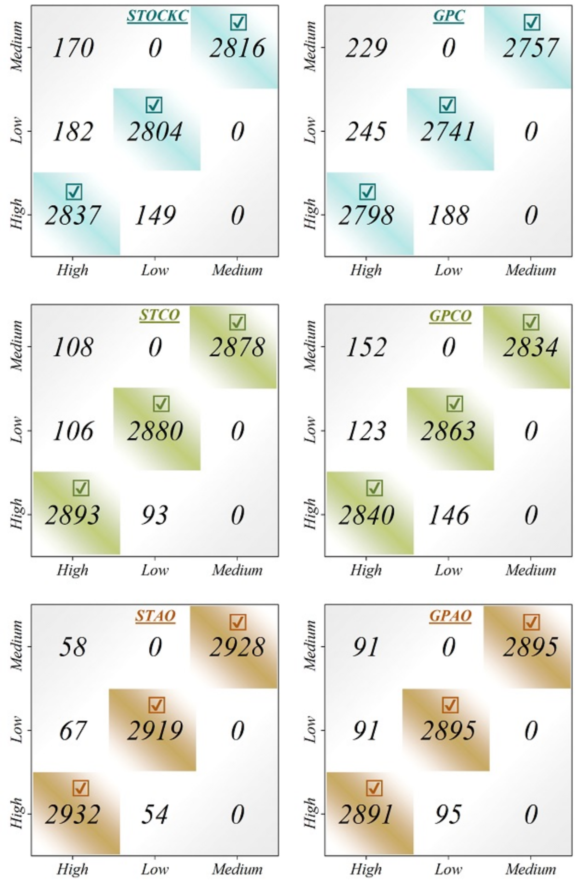


**Fig. 2.** Confusion matrix to determine the misclassification prediction.

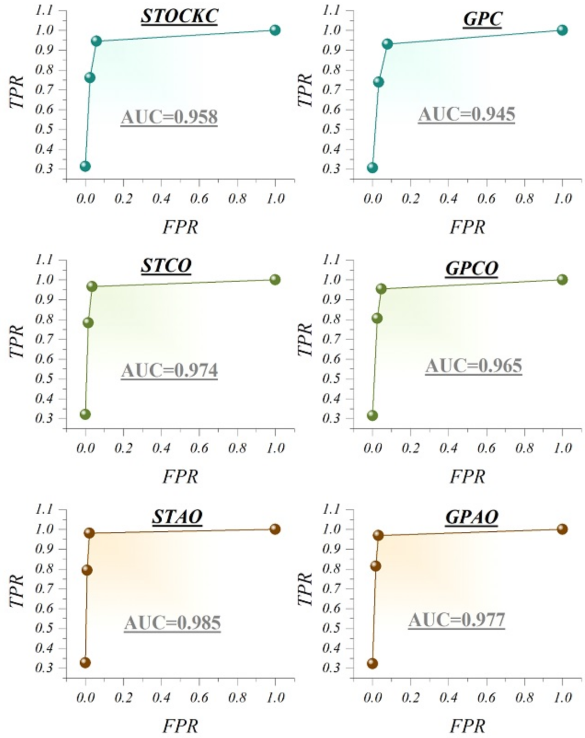


**Fig. 3.** ROC curve for the accuracy of the presented models.

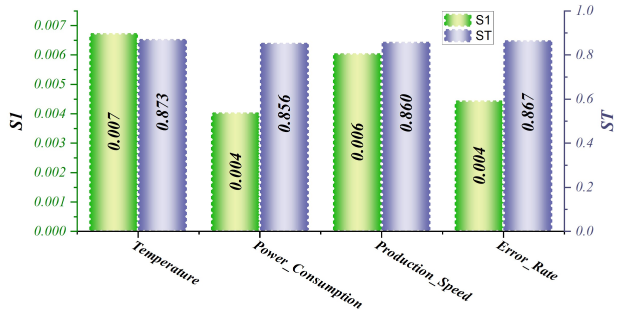


**Fig. 4.** Impact of the input variables on the model's output corresponding to FAST analyses.

itating data-driven, adaptive control of production processes. Their exceptional precision and clarity provide effortless connection with MES and IIoT systems for real-time monitoring, predictive maintenance, and quality assurance. By detecting critical attributes like as production velocity and error frequency, the models provide targeted interventions to minimize waste, enhance throughput, and avert failures. Moreover, their adaptability and resilience under varying conditions boost deployment viability in dynamic settings, providing a scalable option for manufacturers pursuing ongoing process enhancement and operational efficiency in intelligent manufacturing ecosystems.

This SHAP (Shapley Additive Explanations) visualization in Fig. 5 shows the individual and combined contributions of influential input variables to the model output when considering the smart manufacturing case. All features, Temperature, Power Consumption, Production Speed, and Error Rate are evaluated in terms of SHAP value on three levels: low, medium, and high. The most important variables are Production Speed and Error Rate because they have much larger SHAP values. A high Error Rate (up to 3.845) and a high Value of Production Speed (up to 2.829) positively affect the model's output, with both features having a meaningful impact on system behavior. Surprisingly, a medium value of both features also has a helpful effect, whereas a low value has little effect. Temperature and power consumption have relatively small SHAP values and thus have a comparatively weaker effect.

Nevertheless, there are subtle differences across levels of these features, hinting at their non-negligible but indirect impact on performance. Specifically, this study highlights the requirements of smart manufacturing systems to focus on controlling extreme values as much as optimizing intermediate states. Knowledge of how features work together through multiple value ranges enables better decision-making and creates an adaptive, more efficient, and more intelligent production system. The exceptional

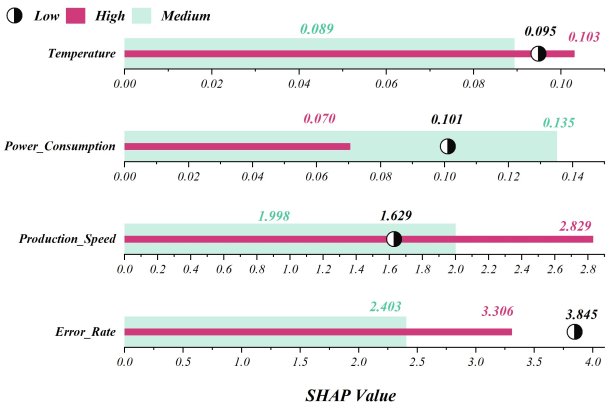


**Fig. 5.** Impact of the input variables on the model's output corresponding to the SHAP analyses.

success of STAO and GPAO is due to their capacity to adeptly record intricate, nonlinear feature interactions. The amalgamation of stacking or Gaussian process classifiers with bio-inspired optimizers facilitates adaptive learning that leverages multivariate dependencies instead of depending on isolated feature effects. The FAST and SHAP studies clearly demonstrate that interaction effects much surpassed individual contributions. These hybrid models adaptively respond to minor fluctuations in operational parameters, enhancing generalization and robustness under diverse production settings.

## 4. Conclusion

The findings of this research emphasize the importance of feature analysis in achieving greater insight into intelligent manufacturing systems. With emphasis on the scrutiny of operational parameters like Operation Mode, Temperature, Power Consumption, Network Latency, Production Speed, Error Rate, and Efficiency Status, this research provides an analytical framework that translates the input data to system output with greater accuracy. Contrary to methods that solely stress the deployment of predictive models, this research explicitly highlights the analysis of the affecting factors and measures the contribution of individual parameters to overall system behavior. Two state-of-the-art classification models, stacking classification (SC) and Gaussian process classification (GPC), were utilized to evaluate the performance seriously. To improve the two models' potential for optimization, two algorithms inspired by nature, Artificial Rabbit Optimization (ARO) and Coronavirus Herd Immunity Optimizer (CO), were utilized. The process led to the construction of four hybrid models: STCO, STAO, GPCO, and GPAO, which have high potential for dealing with the multivariate and nonlinear character of real data in the manufacturing domain. Among these, the best-performing model was the STAO model, with a high accuracy of 0.980 on the training set. Aside from providing accurate classifications, the model successfully determined the most influential operational factors to system productivity based on extensive feature analysis. From this analytical point of view, the interrelations between the conditions of operation and system responses came to be understood in greater depth, making the model applicable to real-time decision-making in industrial settings. As an example, the analysis indicated that the influence of Production Speed and Error Rate was greater, with Network Latency being comparatively less significant. Such knowledge is crucial for the planning of improvement opportunities and optimization in the case of industrial systems. Despite these encouraging findings, even the top-performing model, STAO, is not flawless. Though it performed well in training, more evaluation is needed to ascertain that this model is generalizable to unknown or dynamic conditions. Moreover, model interpretability and scalability are open questions, specifically for real-time applications where computational efficiency is paramount. Subsequent research can incorporate temporal analysis methods to identify dormant patterns, utilize real-time data to drive adaptive learning, and enact interpretability AI (XAI) techniques to shed light on model choices. Additionally, increasing the scope of the dataset to include additional contextual features, e.g., machine age or past maintenance, may enrich model understanding and improve predictive accuracy for a greater variety of manufacturing settings. This research relies on static, synthetic datasets, perhaps constraining its applicability to real-time industrial contexts. The computational complexity of hybrid models may impact their implementation in resource-limited environments. Future research should investigate real-time data integration, scalability assessment, and deployment on edge or cloud-based industrial platforms. Ultimately, the primary goal of this research is to emphasize the necessity for input data analysis and the consideration of how every feature contributes to the overall system performance. By carefully investigating and interpreting the input variables, the main factors that have the most significant contributions to the output behavior can be determined, allowing the construction of models that are more efficient, precise, and more understandable and applicable to intelligent manufacturing.

The suggested models, specifically STAO and GPAO, can be implemented in real-time production settings through integration with MES or IIoT systems. Their minimal misclassification rates and capacity to identify critical performance factors render them appropriate for adaptive control, predictive maintenance, and energy optimization in industrial operations.

## References


[1] C. Li, Y. Chen, and Y. Shang, (2022) *"A review of industrial big data for decision making in intelligent manufacturing"* **Engineering science and technology, an international journal *29***: 101021. DOI: 10.1016/j.jestch.2021.06.001.

[2] A. Barari, M. de Sales Guerra Tsuzuki, Y. Cohen, and M. Macchi, (2021) *"Intelligent manufacturing systems towards industry 4.0 era"* **Journal of Intelligent Manufacturing *32***: 1793–1796. DOI: 10.1007/s10845-021-01769-0.

[3] Y. Shen and X. Zhang, (2023) *"Intelligent manufacturing, green technological innovation and environmental pollution"* **Journal of Innovation & Knowledge *8***: 100384. DOI: 10.1016/j.jik.2023.100384.

[4] G. Nain, K. K. Pattanaik, and G. K. Sharma, (2022) *"Towards edge computing in intelligent manufacturing: Past, present and future"* **Journal of Manufacturing Systems *62***: 588–611. DOI: 10.1016/j.jmsy.2022.01.010.

[5] L. Zhou, Z. Jiang, N. Geng, Y. Niu, F. Cui, K. Liu, and N. Qi, (2022) *"Production and operations management for intelligent manufacturing: A systematic literature review"* **International Journal of Production Research *60***: 808–846. DOI: 10.1080/00207543.2021.2017055.

[6] Y. Fu, Y. Hou, Z. Wang, X. Wu, K. Gao, and L. Wang, (2021) *"Distributed scheduling problems in intelligent manufacturing systems"* **Tsinghua Science and Technology *26***: 625–645. DOI: 10.26599/TST.2021.9010009.

[7] M. Attaran, S. Attaran, and B. G. Celik, (2023) *"The impact of digital twins on the evolution of intelligent manufacturing and Industry 4.0"* **Advances in Computational Intelligence *3***: 11. DOI: 10.1007/s43674-023-00058-y.

[8] K. Feng, J. C. Ji, Q. Ni, Y. Li, W. Mao, and L. Liu, (2023) *"A novel vibration-based prognostic scheme for gear health management in surface wear progression of the intelligent manufacturing system"* **Wear 522**: 204697. DOI: 10.1016/j.wear.2023.204697.

[9] S. Yin, N. Zhang, K. Ullah, and S. Gao, (2022) *"Enhancing digital innovation for the sustainable transformation of manufacturing industry: a pressure-state-response system framework to perceptions of digital green innovation and its performance for green and intelligent manufacturing"* **Systems *10***: 72. DOI: 10.3390/systems10030072.

[10] B. Wang, F. Tao, X. Fang, C. Liu, Y. Liu, and T. Freiheit, (2021) *"Smart manufacturing and intelligent manufacturing: A comparative review"* **Engineering 7**: 738–757. DOI: 10.1016/j.eng.2020.07.017.

[11] B. He and K.-J. Bai, (2021) *"Digital twin-based sustainable intelligent manufacturing: a review"* **Advances in Manufacturing *9***: 1–21. DOI: 10.1007/s40436-020-00302-5.

[12] H. B. Mahajan, A. Badarla, and A. A. Junnarkar, (2021) *"CL-IoT: cross-layer Internet of Things protocol for intelligent manufacturing of smart farming"* **Journal of Ambient Intelligence and Humanized Computing *12***: 7777–7791. DOI: 10.1007/s12652-020-02502-0.

[13] S. Wu and J. Zhang, (2021) *"Research on a compound dual innovation capability model of intelligent manufacturing enterprises"* **Sustainability *13***: 12521. DOI: 10.3390/su132212521.

[14] V. Bortnikova, V. Yevsieiev, I. Botsman, I. Nevliudov, K. Kolesnyk, and N. Jaworski, (2021) *"Queries classification using machine learning for implementation in intelligent manufacturing"* **Publishing House of Bialystok University of Technology**: DOI: 10.24427/978-83-66391-87-1.

[15] Q. Huang. "Intelligent manufacturing". In: Springer, 2022, 111–127. DOI: 10.1007/978-981-19-2527-6.

[16] H.-Y. Zhang, Q.-X. Chen, J. M. Smith, N. Mao, Y. Liao, and S.-H. Xi, (2021) *"Queueing network models for intelligent manufacturing units with dual-resource constraints"* **Computers & Operations Research *129***: 105213. DOI: 10.1016/j.cor.2021.105213.

[17] I. K. Nti, A. F. Adekoya, B. A. Weyori, and O. Nyarko-Boateng, (2022) *"Applications of artificial intelligence in engineering and manufacturing: a systematic review"* **Journal of Intelligent Manufacturing *33***: 1581–1601. DOI: 10.1007/s10845-021-01771-6.

[18] H. Fan, X. Liu, J. Y. H. Fuh, W. F. Lu, and B. Li, (2025) *"Embodied intelligence in manufacturing: leveraging large language models for autonomous industrial robotics"* **Journal of Intelligent Manufacturing *36***: 1141–1157. DOI: 10.1007/s10845-023-02294-y.

**[19]** H. Yang, L. Li, and Y. Liu, (2022) *"The effect of manufacturing intelligence on green innovation performance in China"* **Technological Forecasting and Social Change** ***178***: 121569. DOI: 10.1016/j.techfore.2022.121569.

**[20]** S. W. Kim, J. H. Kong, S. W. Lee, and S. Lee, (2022) *"Recent advances of artificial intelligence in manufacturing industrial sectors: A review"* **International Journal of Precision Engineering and Manufacturing** ***23***: 111–129. DOI: 10.1007/s12541-021-00600-3.

**[21]** B. S. A. Alhayani and H. Llhan, (2021) *"RETRACTED ARTICLE: Visual sensor intelligent module based image transmission in industrial manufacturing for monitoring and manipulation problems"* **Journal of Intelligent Manufacturing** ***32***: 597–610. DOI: 10.1007/s10845-020-01590-1.

**[22]** M. Noor-A-Rahim, F. Firyaguna, J. John, M. O. Khyam, D. Pesch, E. Armstrong, H. Claussen, and H. V. Poor, (2022) *"Toward industry 5.0: Intelligent reflecting surface in smart manufacturing"* **IEEE Communications Magazine** ***60***: 72–78. DOI: 10.1109/MCOM.001.2200016.

**[23]** L. Wang, Z. Pan, and J. Wang, (2021) *"A review of reinforcement learning based intelligent optimization for manufacturing scheduling"* **Complex System Modeling and Simulation** ***1***: 257–270. DOI: 10.23919/CSMS.2021.0027.

**[24]** H. Yan, X. Du, L. Xu, S. Xu, Y. Zhang, and P. Gong, (2022) *"Toward intelligent clothes manufacturing: a systematic method for static and dynamic task allocation by genetic optimization"* **Neural Computing and Applications** ***34***: 7881–7897. DOI: 10.1007/s00521-022-06890-6.

**[25]** X. Zhou, X. Xu, W. Liang, Z. Zeng, S. Shimizu, L. T. Yang, and Q. Jin, (2021) *"Intelligent small object detection for digital twin in smart manufacturing with industrial cyber-physical systems"* **IEEE Transactions on Industrial Informatics** ***18***: 1377–1386. DOI: 10.1109/TII.2021.3061419.

**[26]** A. Shojaeinasab, T. Charter, M. Jalayer, M. Khadivi, O. Ogunfowora, N. Raiyani, M. Yaghoubi, and H. Najjaran, (2022) *"Intelligent manufacturing execution systems: A systematic review"* **Journal of Manufacturing Systems** ***62***: 503–522. DOI: 10.1016/j.jmsy.2022.01.004.

**[27]** J. Wang, C. Xu, J. Zhang, and R. Zhong, (2022) *"Big data analytics for intelligent manufacturing systems: A review"* **Journal of Manufacturing Systems** ***62***: 738–752. DOI: 10.1016/j.jmsy.2021.03.005.

**[28]** T. Yang, X. Yi, S. Lu, K. H. Johansson, and T. Chai, (2021) *"Intelligent manufacturing for the process industry driven by industrial artificial intelligence"* **Engineering** ***7***: 1224–1230. DOI: 10.1016/j.eng.2021.04.023.

**[29]** H. Wang, Z. Ma, W. Qi, N. Zhang, and H. Zhuang. "A Research Review of the Stacking Classification Model". In: *2024 6th International Conference on Machine Learning, Big Data and Business Intelligence (MLBDBI)*. IEEE, 2024, 61–65. DOI: 10.1109/MLBDBI63974.2024.10823722.

**[30]** Q. Bi, H. Zhang, and K. Qin, (2021) *"Multi-scale stacking attention pooling for remote sensing scene classification"* **Neurocomputing** ***436***: 147–161. DOI: 10.1016/j.neucom.2021.01.038.

**[31]** G. Zhao, E. Dougherty, B.-J. Yoon, F. Alexander, and X. Qian, (2021) *"Efficient active learning for Gaussian process classification by error reduction"* **Advances in Neural Information Processing Systems** ***34***: 9734–9746.

**[32]** T. Lan, Z. Zhang, J. Sun, W. Zhao, M. Zhang, W. Jia, M. Liu, and X. Guo, (2022) *"Regional prediction and prevention analysis of rockburst hazard based on the Gaussian process for binary classification"* **Frontiers in Earth Science** ***10***: 959232. DOI: 10.3389/feart.2022.959232.

**[33]** M. A. Awadallah, M. S. Braik, M. A. Al-Betar, and I. A. Doush, (2023) *"An enhanced binary artificial rabbits optimization for feature selection in medical diagnosis"* **Neural Computing and Applications** ***35***: 20013–20068. DOI: 10.1007/s00521-023-08812-6.

**[34]** Y. Wang, Y. Xiao, Y. Guo, and J. Li, (2022) *"Dynamic chaotic opposition-based learning-driven hybrid aquila optimizer and artificial rabbits optimization algorithm: framework and applications"* **Processes** ***10***: 2703. DOI: 10.3390/pr10122703.

**[35]** S. N. Makhadmeh, M. A. Al-Betar, M. A. Awadallah, A. K. Abasi, Z. A. A. Alyasseri, I. A. Doush, O. A. Alomari, R. Damaševičius, A. Zajančkauskas, and M. A. Mohammed, (2022) *"A modified coronavirus herd immunity optimizer for the power scheduling problem"* **Mathematics** ***10***: 315. DOI: 10.3390/math10030315.

**[36]** A. Hosseinalipour, R. Ghanbarzadeh, B. Arasteh, F. S. Gharehchopogh, and S. Mirjalili, (2024) *"A metaheuristic approach based on coronavirus herd immunity optimiser for breast cancer diagnosis"* **Cluster Computing** ***27***: 9451–9475. DOI: 10.1007/s10586-024-04360-3.