Enhancing Product Modelling Process Design and Visual Performance Through Random Forest Optimization

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Abstract: *The design cycle's crucial component of manufacturing process optimization includes issue formulation, modeling, simulations, optimization, and deployment. Simulation methodologies are essential to get actual optimization rather than just process improvements. This study proposes a random forest approach for analyzing and optimizing product aesthetics and integrating new technology into design. Virtual display technology (VDT) lets customers see product performance in detail, making buying easier. VDT improves user experience and product sales. We use a machine learning technique called random forest to handle complex data and make reliable predictions. We analyze and optimize product aesthetics using design components, material choices, and consumer preferences. VDT helps us incorporate new technologies into the design. We tried the random forest (RF) approach for analyzing and optimizing product aesthetics and virtual display technology. Our results show that RF forecasts and optimizations increase product attractiveness. This study emphasizes industrial process optimization and simulation's role in actual optimization. We offer an RF approach for analyzing and optimizing product aesthetics and integrating new technology into design. VDT improves software capabilities and gives users a complete understanding of product performance. The outcomes of the proposed system have provided 95% accuracy, 94% precision, and 98% recall which enhance process effectiveness and user experience.*

Povzetek: Študija predlaga pristop z naključnim gozdom za optimizacijo estetskih vidikov izdelkov in vključitev virtualne prikazne tehnologije (VDT) v oblikovanje.

1 Introduction

In the setting of product innovation, analysis results relate to forecasts of the market states in response to external demands. They are often used in industrial environments by conducting finite element studies on the product geometry produced by computer-aided software architecture. Its expansion has also been aided by the widespread availability of high-performance, low-cost personal computers and enterprise applications [1]. Figure: 1 represents the structure of the product design process model. The rapid growth of internet commerce over the last ten years has opened up various possibilities and led to fundamental shifts in businesses creating positioning and pricing their goods. Environmental problems that never go away and sporadic energy catastrophes are major worries for the sector. For companies to succeed in today's competitive global market, growing their line of profitable and useful items is essential.

The industry needs help with predicting the life cycles of the products in an unpredictable competitive environment. New device creation is necessary to satisfy client requirements in a short time. Any component of product design, including sales promotion forms and contents, may act as a driver in the market environment to configure a product's extrinsic characteristics [2]. A summary of an optimization method using a Japanese methodology for lean manufacturing is shown in Table 1. Lean management focuses on producing just activities that bring value and decreasing everything else; it should be expressed in the conclusion. Every move that the client, for whom the product or service is intended, can assess as required and desirable is a value-adding action.

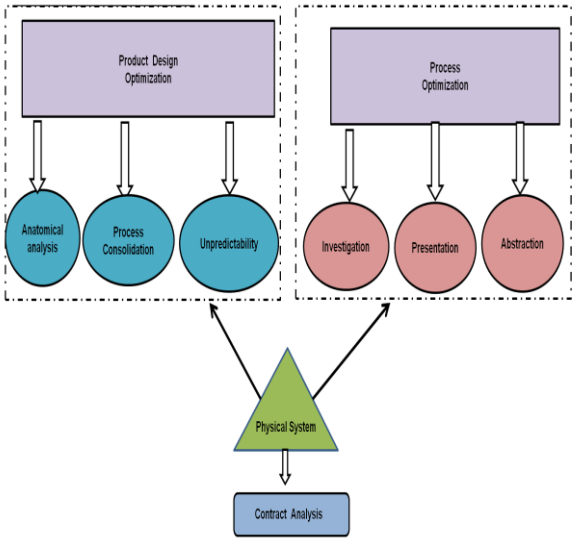

Figure 1: Structure of product design process model

Table 1: Types of process optimization

S.NO	Types of product optimization
1	Equipment optimization
2	Procedure optimization
3	Control optimization

Other factors considered throughout the optimization procedure are shown in Table 1. The production process system was broken down into three primary components: the material that made up the system, the procedures that connected the material to produce the supply chain, and the controllers that oversaw the operation of the first two components. Three planning factors should be considered throughout the optimization process: geometry, material, and installation technique. When employing a CAD/CAE class system to determine the shape of process items, the geometrical parameter is considered. Further detailed analyses, such as dynamic and strength analyses, have been introduced to this approach. While optimizing materials, the second component is taken into account. For kinds of production systems, this is very crucial. With the right assembly process and assembly parameters, at least the final factor that affects a product's characteristics is considered.

Changes in the design of intricate manufacturing processes often occur unexpectedly, and they may substantially influence the product development cycle via the propagation of these design activities. Designing the best route to shorten the design process is thus crucial. Creating products is a knowledge-intensive activity that is essential for manufacturing companies. Design elements influence a product's overall cognition. To satisfy client demands, rapid product development is required. As a component of product quality, functional product design seeks to produce goods that benefit consumers. Improving product design techniques is a fascinating topic in academic and business environments. Making client satisfaction a baseline for product quality is the goal of efficient product design [3]. Modern design methods are more interactive and experience and understanding than ever before. A product family is a collection of connected goods that fill various market gaps and have similar features, components, and subsystems. Several quantitative models have been put forward during all stages of platform product innovation [4].

The term additive manufacturing (AM) refers to a collection of fabrication techniques used for fast prototyping. Today's society is more interested in creativity. Effective strategies that motivate product designers are thus highly desired. Visualization is one of the useful strategies [5]. Creativity is just connecting things, according to Steven Jobs. Convolutional neural networks, a kind of deep learning technique, have recently achieved advances in several domains, including computer vision, and are used extensively in object identification, detection, and segmentation [6]. In addition to physical and operational skills, manufacturing processes also call for efficient use of resources like time and raw materials. By anticipating the best (optimum) process settings that use the least amount of material and take the least amount of time to produce, the performance of the manufacturing process may be further enhanced. An increasingly popular method for making predictions based on training data and sophisticated algorithms is machine learning, a subset of artificial intelligence [7]. Machine learning prediction skills may be used in the manufacturing sector to choose the optimum process variables that would ultimately result in the lowest cost while maintaining the highest product accuracy and quality standards. The objectives of Industry 4.0 would be more easily attained with the automated prediction of optimal process parameters during manufacturing [8].

Traditional approaches could be more efficient and accurate, resulting in better designs and slower processes. The study uses random forest optimization to enhance product models' visual appeal. In product modeling, algorithms based on random forests can improve decision-making, repetitions, and design outcomes. This study uses these methodologies to revolutionize product design and provide professionals in the industry with vital insights. Our study aims to provide a random forest method for analyzing and improving product aesthetics and incorporating new technology into the design process. To strengthen software capabilities and deepen our grasp of virtual display technology, we plan to investigate the virtual display of smart objects.

The accuracy of the assault detection is improved using random forest. The study shows how product design optimization boosts its efficacy via machine learning and the field's applicability to trial-and-error decision-making. The RF is especially suitable for assessing and forecasting several elements of product design related to visual

aesthetics and functionality due to its capacity to handle complicated information, endure with non-linear correlations, and minimize over fitting. Through the use of RF, designers integrate data-driven findings into their product development strategies, improve design outputs, and make well-
informed decisions that ultimately improve the user experience.

Contribution of the study:

- The process design approach based on a particular learning technique is assessed.
- An effective random forest model is recommended to promote the visual performance that is optimized material layout within a given design space and evaluate the efficiency of the process.
- VDT and the RF technique together improve product appearance, encourage industrial process simulation and optimization, and expand software options.

The literature review that formed the foundation of our investigation is presented in Part 2 of this study. Next, the method we used to gather our results for Segment 3 will be discussed. We offer and discuss the findings in Segment 4. Segment 5 concludes the study's relevance, constraints, and suggestions for more investigation.

2 Literature survey

Lot of researchers had developed machine learning and deep learning algorithm for many applications. among them some of the works are analyzed in table 2.

Table 2: summary of literature survey

Reference	Objective	Finding	Limitation
[9]	The research suggested a Chinese character packing quality detection technique using a lightweight convolutional neural network (CNN) and machine vision.	The new packaging series is created to fuse Chinese character art design and classical culture, together with theoretical research and case studies.	CNNs require a large amount of training data to generalize over a wide range of designs.
[10]	The article summarized the complete message and anticipated the potential uses and upcoming trends for information visual reality (VR) technologies in digital art goods.	The findings demonstrate that the former performs better than the latter two methods and performs well while analyzing imbalanced data, which attests to the effectiveness and efficacy of the algorithm model.	Tactile input is required for analyzing texture and substance in packaging design.
[11]	The study offered multilayer perceptron genetic algorithm neural network (GA-MLP-NN) for product form assessment.	The article demonstrated the dependability of model performance.	GA-MLP-NN struggled with complicated design variants owing to its poor pattern recognition capabilities.
[12]	The study used a customized product technique based on a Bayesian network (BN).	The issue of incomplete and incorrect expression can be solved, and the connection between the product's performance and consumer demand may be improved.	Precise modeling in package visuals and style is restricted.
[13]	The research focused on two methods for processing images that use a salient object detection technique.	It concluded that blind people might enhance their item recognition skills with the help of a visual prosthesis.	It ignores complex patterns that were essential to visual style and product packaging.

[14]	The paper addressed the business and designer pain points by integrating computer technologies, big data, IoT, parameterization, and artificial intelligence into industrial design and production processes.	Decrease design cycles for the industrial environment and health design by utilizing a cognitive brain neural network platform.	Security and privacy issues were among them.
[15]	The article enhanced the designer's inefficient and redundant labor efficiency, and designers can transition between different tasks.	Parallel to a particular article, an expert manufacturing environment and health design process is developed.	Intricacy, difficulties with integrating, and poor compatibility.
[16]	The research focused on vision influences human upper-body posture, modeling head-neck motions and researching the subtleties of vision and eye movements.	The method solves an optimization issue once for a certain posture or job, using human performance assessments to produce objective functions.	It disregards intricate patterns that were crucial to the visual aesthetic and packing of the goods.
[17]	The article developed that Visual dispersion and visual acuity are two new performance metrics.	It generally discovers that posture was not controlled.	The possibility of performance overhead was one of the primary drawbacks.
[18]	The research investigated and analyzed the properties of video data.	A method for storing surveillance footage on university campuses as a particular application setting.	It was unable to repeatedly read the same instructions.
[19]	The study suggested the main subject matter of the video was reflected in its key frame.	A stochastic Petri net was used to verify the storage system, and a quantitative method was used to confirm the improvement in query performance.	Maintaining visual coherence requires careful consideration of location, frequency, and interpolation approaches.
[20]	The article suggested multi-objective optimisation (EMO) for the creation of several products with similar parts, modules, and subsystems but distinct market niches and consumer groups, known as the product family design.	The main difficulty in creating a family of goods is to address the inherent trade-off between performance and commonality.	Complexity, expense of computing, and determining the best solutions because of several purposes.
[21]	The research presented many-objective visual analytics (MOVA) for resolving trade-offs between commonalities and several performances.	Goals based on many-objective evolutionary optimization and visual analytics.	The overwhelming visual depiction of complex data sets impedes efficient analysis and decision-making.

[22]	The article introduced the audience to visual analytics and investigated how and where Visual reality might be used for visual analytics.	The study focused on the challenging questions of identifying what it would take to integrate Visual reality technology into the funding stream for visual analytics research.	Screen resolution, processing power, and interface complexity.
[23]	The research preferred virtual product appearance technologies.	To create a specific design approach may overcome the constraint of combining forms and colors to create a fresh, unique, and dynamic product image.	Realism, interaction, and restrictions on sensory engagement were features of virtual displays.
[24]	The research was utilized scheduling design tasks for job distribution among designers.	The study does not take into account various design methodologies for various product types to enhance designers' effectiveness.	Difficulties in allocating resources and effectively distributing the burden.
[25]	The article was represented as par-v-Support Vector Regression (SVR).	Probabilistic restrictions may be incorporated with prior information about the maximum completion time, specifying the target value's neighborhood size.	Precisely simulating intricate interactions that affect the efficacy it is in virtual display situations.
[26]	The study suggested a set of metrics and interpretation fundamental modeling approaches to pinpoint the forces that drive and are influenced by effective supply chain management.	The framework of expertise administration to enhance the efficiency of businesses.	Improving accuracy and reality in virtual display systems requires basic modeling.
[27]	The paper offered a complete reference model that was grounded in the notion of Skin Model Shapes.	It functions as the production and design process's digital counterpart for the actual goods.	Limit accurate portrayal and could affect the user experience.
[28]	The study presented a brand-new machine vision evaluation method based on deep learning.	The research findings were precisely recognizing and classifying defective items.	Intricate visual interactions that need for more advanced models in order to accurately portray.
[29]	The paper suggested the Stimulus-Organism-Response (S-O-R) method.	Application layout and app functionality attributes stimulate user involvement with travel apps.	Neglects the many cognitive processes that occur during user interactions.
[30]	The study improved the organizations' compliance with Circular economy (CE) standards by introducing a new	To integrating the operations and systemic perspectives into business choices and empowering organizations to approach	Technologies for virtual displays due to their complexity.

	approach termed backcasting and eco-design for the circular economy (BECE).	the CE in its entirety, BECE increases the possibility that its execution will be effective.	
[31]	The paper investigated small and medium-sized enterprises (SMEs) that go through a digital shift have higher performance.	Devote more money to business model innovation and participate proactively in the execution of strategies.	Financial limitations and demand for technological expertise.

3 Materials and method

This section begins by describing the data gathering and preparation procedures. The procedure for conducting feature evaluations is then described, followed by the RF-based framework for enhancing product modeling. The performance indicators are used to assess categorization results. Figure 2 depicts the architecture of the proposed method.

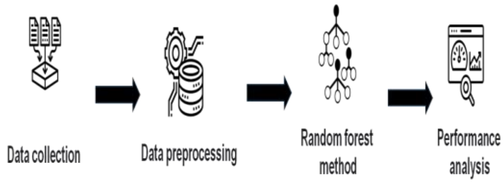

Figure 2: Framework of the proposed method

a. Data collection

A 2008–2009 Chinese survey tested the ideas above. China is an attractive rising market for this research because of its population, rapid economy, increasing individual demand, and global industrial and supply chain hub position. China is huge, making it hard to get specimens from everywhere. Regional industrial development and commoditization also vary. The key manufacturing provinces surveyed were Guangdong, Shandong, Shaanxi, and Henan. Guangdong had the most companies and world-class manufacturing. In the Pearl River Delta, Guangdong has seen more economic liberalization and marketization. Northern Chinese Shandong is industrialized. Its economic growth mirrors China's average. Shaanxi, a northwestern interior Chinese province, was a pre-industrial building site. Henan is an agricultural

production province in central China. Hence, these four provinces indicate distinct Chinese areas with varied industrial development, market systems, and commoditization.

b. Data pre-processing

The procedure for design and visual performance of product modelling that are greatly improved by pre-processing using Z-score normalization. It standardizes the variables, efficiently scales and aligns the data, to improve the modelling accuracy and efficiency. By lowering biases and inconsistencies, this pre-processing stage contributes to more trustworthy and significant insights about visual performance and product design. Z-score normalization greatly improves the overall quality of visual results and optimizes the overall modelling process. The normalizing technique was used to scale down the characteristics during data preparation. Within a feature, the range of values is frequently rather broad, from 0.01 to 1000. When values are normalized, they are scaled down to substantially small numbers. Several methods, including those based on neural networks and RF, rely on this property. In this context, the two most typical approaches are:
Using a min-max distribution:

$$Z = \frac{z-min}{max-min} \quad (1)$$

When the original is, the feature value and $zmin$ is the adjusted one.

$$Z = \frac{z-mean}{stand\_dev} \quad (2)$$

Where the Z-score normalization method is mentioned.

c. Analysis of the Random Forest method in product design

The VDT has produced encouraging results while employed with RF technique to evaluate and improve product aesthetics. The result shows that large improvements in product attractiveness are achieved by RF forecasts and adjustments. The significance of utilizing simulation and industrial process optimization methods to provide observable optimization results is emphasized. It also suggests using RF to assess and improve product aesthetics while incorporating new technology into design in an easy-to-use manner. Virtual display technology improves software capabilities and allows the users an accurate representation of product performs, that help designers and developers make better decisions while designing and developing new products.

An RF is a group of decision trees (DT) that must be trimmed. Each tree is built using a unique bootstrapping data set consisting of randomly picked examples, with the best attributes from each group being used to divide nodes. RF is more resistant to modeling over-fitting and information noise due to these two sources of uncertainty. RF is often used for classification issues, but it may also be adapted to regression tasks. In contrast to the RF classifier, where a label collection represents the tree predictors, the trees in a regression-based random forest take on integer values. The RF predictor is constructed by averaging the forecasts of the trees in a user-specified number of forest plots. For the classification problem, assuming that training data $T\,D = (Y1, Z1), (Y2, Z2)\ldots(YPYP, ZPZP)$ contain P observational data, Yi stands for the input signal owing M features as$Yi = (yi1, yi2\ldots yiQ)$, Yi is the output scalar, and algorithm1 describes the procedure for creating an RF classification method. Creating multiple de-correlated DTs is the primary goal of the RF tutorial mode. The RF adopts the overlap sampling technique called "bagging" to reduce the classification-related variation. In particular, it removes observations with substitution from the trained dataset to produce the independent validation set. After that, various bootstrap samples may be used to educate each decision tree, increasing the variety of the trees.

Algorithm 1: RF classification method

1: **procedure**: RF classification
2: for $i = 1\ to\ I$: $(I\ am\ the\ number\ of\ CST)$
3: Design a bootstrap experiment AT_i with M observations from $T\,D$;
4: Accept a treeCS_i related to its AT_i:
a. Gather all of your observations and begin dividing a node of AT_i
b. Iterate the following steps on each remaining node recursively:
i. Specify at Heuristic$n$ features (m < M) from N candidates: $n \leftarrow N$
ii. Find the Procedure j feature split that minimizes impurities the most, given a set of m potential splits.
iii. Divide this component into two smaller nodes in Step ii using the split solution found in Step ii.
5: Putting together all DT trainees at the base level $g_i(.)$ will provide a well-trained RF (.).
6**: end operation**
7: **operation:** RF Classification
8: For a good observation V_{new}, the output $QE\ (V_{new})$,
Of RF is predicted by:

$$QE\ (V_{new}), = argmax_Z \sum_{i=1}^{I} J(\bar{g}_i(V_{new}) = V)$$

Where $\bar{g}_i(V_{new})$is the outcome of predicting V_{new} using the jth DT. $J(.)$is a zero-one judgment, where$J(\bar{g}_i(V_{new}) = V) = 1$, and the argmaxZargument returns the class with the highest version numbers among all DT.
9: **End**

Moreover, rather than choosing randomly from all Q features, the optimal split of each node is generated by picking m subset characteristics to further limit the correlations across different DT. Because of this, DT in RF may be expanded without pruning, reducing computational overhead. Moreover, by averaging several de-correlated DT, it is possible to enhance the transient stability of RF by utilizing multiple variants and node attributes.

For each DT in an RF, the bagging approach would repeatedly cause the same training data to be used as the bootstrap sample, leading to some insights being overlooked for this DT. These data points are "out of the bag" (OOB) samples. Around a third of the total TD comprises OOB samples that would be discarded throughout the RFRF training procedure. Consequently, the OOB samples may be used to assess the DT performance of the classifier each time it has been trained. This allows RF to make accurate predictions without relying on biased training data.

d. Visual improvement program for product appearance design

While corporate brand design and athletic events are two of the most prominent examples of how visual identity design has developed and evolved over the years, the usage of graphic structures in public spaces and modes of transportation has also played a significant role. Visual language design is a tool for understanding and sharing information; it's an innovative approach to improving how we convey our thoughts and feelings to one another. To effectively communicate complex social and economic problems to the public, symbolic graphics are advocated as part of a comprehensive graphic design system for the greater good. The Aesop System is a visual communication method based on the “International Graphic Education and Graphic Design System principles." The plan resulted from cooperation between the Dutch government, architects, and Neurath, who tested and refined their proposed visuals until they found those that best communicated the system's purpose and were familiar to the widest possible audience.

$$Q_{ji}^{M} = 1 - Q_{ji,} \tag{3}$$

$$ {}_{b}^{H}C_{s}^{x}e(s) = \lim_{g \to 0} \frac{1}{g^{x}} \sum_{n=0}^{[s-b/g]} (-1)^{n} \frac{\Gamma(x+1)}{n!\Gamma(x-n+1)} e(s-ng) \quad (4) $$

Virtual performance, real-time interaction, and 3D positioning are the three primary components of RFRF technology's visual impact. Once the user performs a physical action, a virtual 3D picture is shown in the user's field of view. Finally, the virtual surroundings and the integration of the actual scene achieve a higher level of fitting to restore the virtual image's feeling of depth in the real world. Second, the impact of two-way interoperable conversation may be amplified from its initial one-way state using real-time engagement, which can be built from basic facial expressions and single computerized communication. At long last, 3D positioning can instantly supplement the physical environment. With video-based augmented reality applications, for instance, the camera's feed may be presented on the screen in real time, allowing users to verify the authenticity of the environment.

Quantitative research about the manufacturer's modeling and color is reflected in the 3D model and color data. Understanding the dissimilar features of the two data types is a prerequisite for effectively realizing data fusion in practice. It is important to note that there may be substantial discrepancies in the gist of the data when comparing various main components and that the numerical data acquired by the 3D modeling statistical and mathematical formula are commonly stated as continuous real values. Color data derived from the color quantized physical equation are likewise numerical but are often expressed as constant integers, and their information boundaries are less dissimilar. Instead of integers, real numbers are more suited for quantitatively evaluating object 3ds max and color features due to their ability to quantify parameters with continuous fluctuation characteristics.

Creating a 3D shape with an image in mind is a primary need for the imagery design of products. To simultaneously achieve the goal of developing new 3d objects based on complex-valued coefficients decrease and generalization of the target imagery, this section presents a method for producing product 3D imagery forms that are principally focused on the growth of CVAE. CVAE's multilayer perceptron neural network structure allows it to express complicated causal relations more successfully, allowing it to learn relevant data with greater representative democratic execution increased D information and displaying improved information lowering and sweeping expansion growth. Namely, the identification network's output helps finish the modeling imagery's localization, and the production network's work helps generate new modeling data by integrating external circumstances. We employ the goal graphics data as an environmental factor to create fresh 3D models that adhere to the existing target images and feed them into CVAE with the 3D modeling primary component information. The completed Pareto presentation group of resolutions consists with several distinct presentation solutions that include the computed scores of inter-imagery descriptors after completing the automated computation of the inter-optimum design component for packaging design.

Product ergonomics involves providing end-users with direction through sensory information, gathering more perceptual assessment of the product's many features, and then using statistical engineering approaches to translate that knowledge into design inputs. Consumers may be guided through articulating their requirements and desires with sensory engineering concepts and techniques, which can help them have a richer emotional journey. As a result of the user's subjective assessment of the manufacturer's presence, coloring, substance, and other elements, the designer is capable of accurately obtaining the customer's emotions and potential needs, allowing the developer to optimize the customer's interpretive needs and increase the viewer's having gained. Using a quantitative methodology, perceptual engineering investigates how different design elements relate to one another from the end user's perspective, translating their perceptions of product lines into conceptual design or parameters. This allows for effectively integrating user feedback into creating new products and services.

4 Result and discussion

4.1 The impact of RF on product design effectiveness

Designing a product around the needs of the consumer is essential. By the study orientation of the virtual display design skills, the user perceptual are mostly used the trials about products into notch exhibit as well as the use of interactive systems into method of exhibiting the environment.

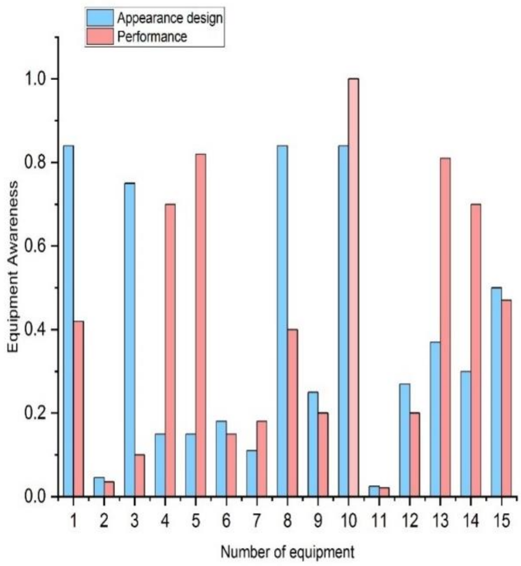

Figure 3: Comparison of cognitive effort

There are three main types of user experiences: the interactive experience, the sensory perceptions, and the emotional reaction. These three phases are a progression from beginner to expert, and they are interdependent, enhancing, and limiting one another. To pique consumers' interest, we must design displays that appeal to their sense of self and emotions, elicit a favorable emotional response, and ultimately lead to a purchase. As shown in Figure 3, user experience is the backbone of the large display and should be the focus of all screen design efforts

4.2 The effects of using visual optimization techniques on product appearance

Each sample's spherical vertices dimensions are used to calculate its spectral coefficients using the spherical Fourier transform. Here, we find that I=30 is the sweet spot for aesthetically pleasing 3D model rebuilding by checking out a range of resonant components on each sample. Figure 4 shows the sample's influence on 3D modeling reconstructions at various harmonic frequencies. Higher harmonic frequencies provide finer and more numerous surface characteristics during reconstruction. Visually, the recovered model is accurate enough at I30 to convey the essential 3D modeling features found in the initial model, and the shape noise is manageable. This harmonic frequency is used to determine the spectral components of the whole sample.

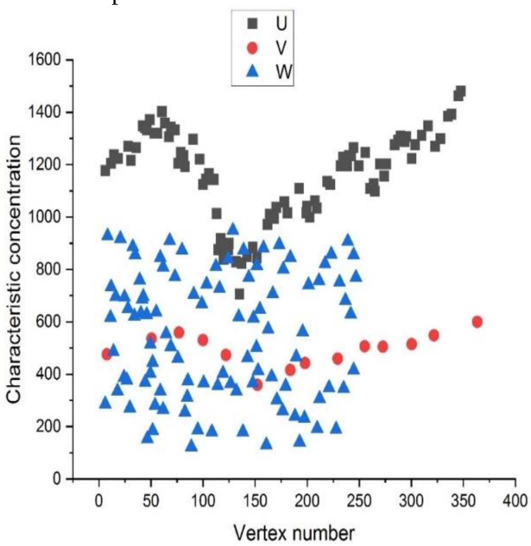

Figure 4: Comparison of application outcome

Table 3: Application outcome

Vertex Number	W	V	U
0	1177.012523	475.5767389	285.7764678
50	1371.835864	535.1359922	402.7422303
100	1124.987874	530.1129227	366.5043714
150	883.5217451	473.0652041	613.3523611
200	1041.748436	441.8504148	231.240284
250	1194.952058	459.7899489	769.0675173
300	1223.655312	514.6849233	-
350	1480.908232	548.4112475	-
400	-	600.0771058	-

The combination of virtual display technology with the RF method improves the look and feel of products, encourages simulation and industrial process optimization methods that expands the possibilities of software. The proposed method RF compared with the other existing method including Genetic algorithm (GA) [24], Support vector regression (SVR) [25], and Virtual reality (VR) [23]. When the models had been trained, their accuracy was evaluated using current image information. Accuracy, precision, recall, and prediction model mean square error (MSE) were the four statistical metrics we utilized to assess the models. Accuracy assesses the entire validity of the design assumptions by comparing properly anticipated occurrences to all other occurrences. Precision in product design refers to the design capacity that prevents erroneous results while identifying and considering the most significant elements or attributes. Recall demonstrates its ability to properly record all relevant facts linked to product design and visual performance without ignoring critical factors.MSE analyzes the model accuracy in predicting real values, delivering useful information into its predictive performance.

4.3 Accuracy

Accuracy is the capacity of a measurement system to provide a precise reading. It indicates how near a measured value is to the real deal or some benchmark. It is also the degree to which a given measurement agrees with a predetermined standard. It is expressed in equation (5),

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

Accuracy is often reported as a fraction or percentage of the entire. Inaccurate forecasts may be made using either the currently used approach or the suggested method. Both systems are aware of the risk. Whereas GA [24], SVR [25], and VR [23] only attain 67%, 88%, and 74% accuracy, respectively, the recommended approach, RFRF, obtains 95% accuracy. As a result, the suggested method is the most reliable option. In Figure 5 and Table 4, we can see how accurate the proposed method.

Table 4: Numerical outcomes of Accuracy

Methods	Accuracy (%)
VR [23]	74
GA [24]	67
SVR [25]	88
RF[Proposed]	95

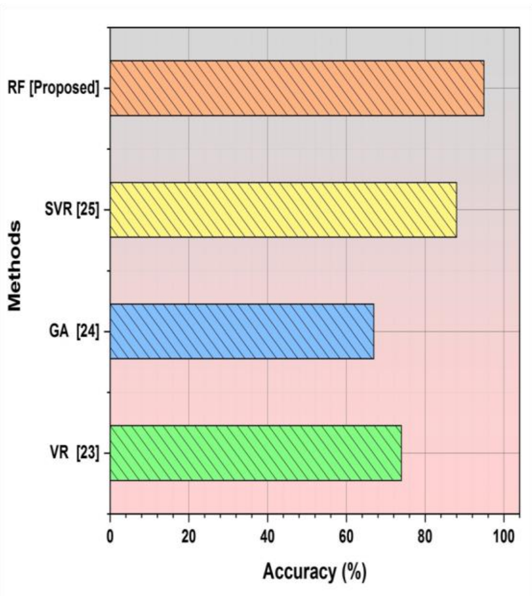

Figure 5: Comparison of accuracy

4.4 Precision

The term "precision" refers to the percentage of correctly detected classes [32]. We verified how many accurate model predictions were found among all the forecasts made. Equation (6) provides the method we used to determine the reliability of the models.

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

Table 5: Numerical outcomes of Precision

Methods	Precision (%)
VR [23]	82
GA [24]	63
SVR [25]	75
RF[Proposed]	94

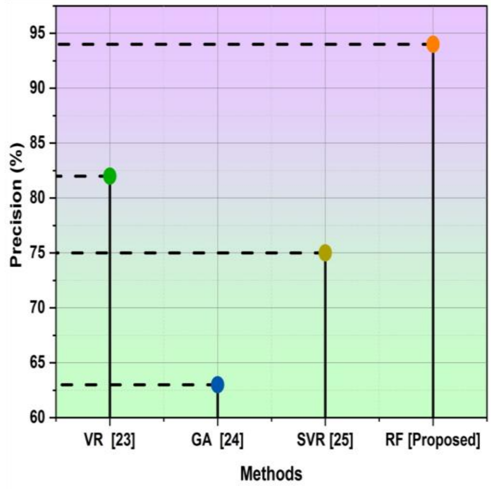

Figure 6: Comparison of precision

A comparison of the precision between the suggested and traditional procedures is shown in Figure 6 and Table 5. GA [24], SVR [25], and VR [23] earned 63%, 75%, and 82% compared to the well-known techniques; however, the suggested method (RF) scored 94 percent. This aspect personally adds to our suggested method's noticeably improved performance.

4.5 Recall

Efficiency in recall reflects how many real-world categories were accurately recognized. We quantified the extent to which the categorization models encompass the items. To determine the models' recall, we used the method in equation (7).

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

A comparison of the recall between the suggested and traditional procedures is shown in Figure 7 and Table 6. The proposed method RF achieved 98% compared to the existing methods including GA, SVR, and VR scored 66%, 87%, and 75%. This component directly contributes to our proposed approach's noticeably enhanced efficacy.

Table 6: Numerical outcomes of Recall

Methods	Recall (%)
VR [23]	75
GA [24]	66
SVR [25]	87
RF [Proposed]	98

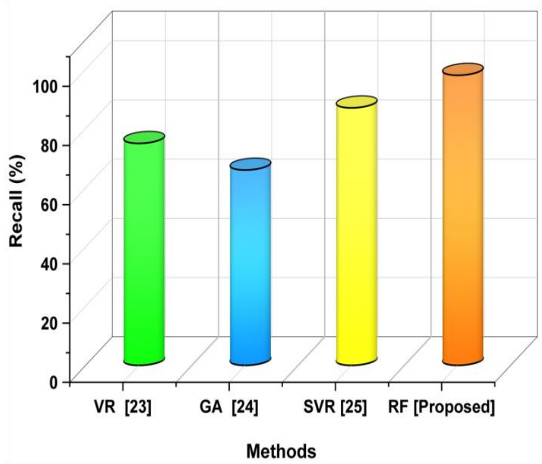

Figure 7: Comparison of recall

4.6 Mean square error

The MSE measures the average square deviation between the expected and forecasted values. This is a popular choice since greater mistakes have larger squared inputs to the mean error, and the value is suitable for various regression situations. Equation (8) provides the formula for determining MSE.

$$MSE = \frac{1}{M\sum_{i=1}^{m}(xi-yi)\dot{2}} \tag{8}$$

Table 7: Numerical outcomes of Mean Square Error

Methods	MSE (%)
VR [23]	93
GA [24]	75
SVR [25]	87
RF [Proposed]	60

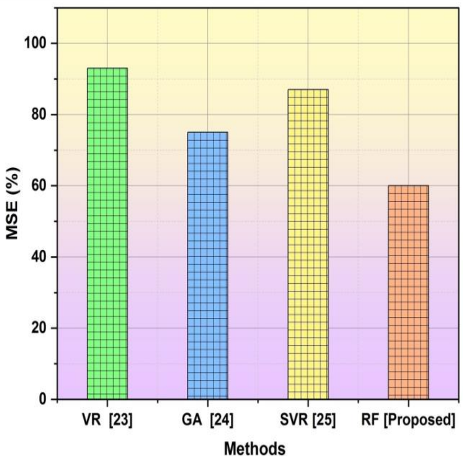

Figure 8: Comparison of mean square error

A comparison of the MSE between the suggested and traditional procedures is shown in Figure 8 and Table 7. On the other hand, GA, SVR, and VR all produce MSE values of 75%, 87%, and 93%, respectively, when used as indicated techniques. The recommended RF method has a lower MSE value than the current techniques. It proves that the suggested strategy is more effective.

5 Discussion

The initial cost of VR [23] hardware and software is one of the main obstacles, which was excessive for certain firms to afford. Furthermore, VR technology demands a lot of processing power, which cause problems or technological limitations for some systems. Additionally, a user's experience in VR settings differ based on issues such as motion sickness or discomfort after extended use, which affect the way for the visualization and design processes work. One drawback is their dependence on population size and generation count that have a huge effect on the rate of convergence and quality of the final solution. Furthermore, GA [24] is unable to perform well in high-dimensional or complicated search spaces that result in less-than-ideal outcomes or an early convergence to local optima. Selecting the right encoding schemes and genetic operators for a given task is difficult and time-consuming.

The sensitivity of SVR [25] to parameter choices, including kernel type and regularization parameter that is one of its main drawback. A poor choice of these parameters causes the data to be either overfitted or underfitted, which would reduce the model accuracy. Furthermore, because SVR is time-consuming to train and takes a lot of processing power, it does not perform well on large lists or datasets with noisy characteristics. The combination of RF method with virtual display technology results in a notable improvement in product aesthetics. By forecasting and adjusting, it increases the appeal of product while highlighting the value of simulation and industrial process optimization techniques. By improving software capabilities, it helps designers to create better products.

6 Conclusion

The formulation of the problem, modeling, simulations, optimization, and deployment are the essential steps in the design cycle of optimizing the manufacturing process. Simulation approaches are crucial if you want real optimization rather than merely process improvements. This study suggested using a random forest approach to analyze and improve product aesthetics and incorporate new technology into design. Through the vitalization of intelligent objects, we hope to gain knowledge about virtual display technologies and enhance the software. We were able to determine the following performance metrics for the suggested method: Accuracy (95%), Precision (94%), Recall (98%), and MSE (60%). The outcomes of the studies demonstrated that the suggested method was effective successful when compared to the one that is currently being utilized. Simulation is the first step towards a fully automated manufacturing system that optimizes itself. Visualization technology can help monitor system operation. ML methods are needed to speed up computations and avoid the globally optimal issue. Future research should include linking and analyzing sensor data for RF operations. This lets virtual devices simulate real-world conditions. Technical limitations, technology, and design complexity restrict the design and visual performance of the product modelling process, but aesthetics, graphical representation, and user interface design are essential. Future study will concentrate on the design of product modelling process and visual performance, with an emphasis on the functional and technological components necessary for success and market competitiveness.

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