Pak. j. life soc. Sci. (2024), 22(2): 17208-17222 E-ISSN: 2221-7630;P-ISSN: 1727-4915

Pakistan Journal of Life and Social Sciences

www.pjlss.edu.pk

https://doi.org/10.57239/PJLSS-2024-22.2.001251

RESEARCH ARTICLE

Visual Communication Style Analysis Combined with Computer Learning and Ceramic Packaging Design Innovation

Bowen Peng*

Jingdezhen Ceramic University, Jingdezhen, 333000, China

ARTICLE INFO

Received: Sep 12, 2024

Accepted: Nov 28, 2024

Keywords

Ceramic Packaging Design Innovation

3D Convolutional Neural Networks (3D-CNNs)

Adaptable Support Vector Machines (ASVM) for color extraction

Visual Communication

K-Means clustering (KMC)

***Corresponding Author:**

pbwjcu@163.com

ABSTRACT

Ceramic packaging design integrates both the aesthetic value and the practicality of packaging designs into the production of the most enduring and artistic packaging materials. This field has adapted to the computer age with a harness for sustainability and efficiency while maintaining aesthetic qualities. The study explores the integration of machine learning (ML) approaches to advance ceramic packaging solutions. The objective is to improve an advanced ceramic packaging design (ACPD)-model employing artificial intelligence (AI) technology. Data for the study were obtained through images and design specifications of ceramic containers, along with user feedback on color and shape preferences. The study applies 3D Convolutional Neural Networks (3D-CNN) for shape reconstruction, Adaptable Support Vector Machines (ASVM) for color extraction, and K-Means clustering (KMC) for multivariate statistical analysis. 3D-CNNs enable the precise reconstruction of complex ceramic container shapes, optimizing design for both form and function. ASVM is used to classify and extract color features, reflecting emerging consumer trends and preferences in ceramic packaging. Additionally, KMC is used to analyze and group design data based on shape and color characteristics, uncovering hidden patterns and relationships that drive design decisions. The combination of AI computations and traditional craftsmanship improves product packaging through better structural design, optimized resource usage and reduced environmental impact.

INTRODUCTION

Visual communication has become an important feature of design in traditional society, mainly in those areas where designs impact customers' choices [1]. A modern strategy is to visual communication regarding package design in ceramic products may improve the looks of the product and deliver a comprehensible indication of the item's identity, worth, and function. Ceramic packaging is a versatile and environmentally friendly option in the packaging industry and it has become a narrative, branding and user experience through the fusion of tradition and innovation [2]. Visual communication encompasses the use of composition, color, typography and images as media in passing a message. Ceramic packaging improves cultural narratives, elicits feelings, and enhances brand link while offering the utility of the packaging. Even though simple forms accompanied by simple shapes provide elegance to novices, complex patterns based on geometry with historical influences create tradition [3].

Ceramics packaging has been made functional and creative by designers as the essence of real adding value, working, and aesthetic elements into its packaging, by improving the material of ceramics [4].

Digital printing and glazing, along with laser engraving, have been used to enable complicated designing, which was not earlier possible. These innovations allow for added value and bringing the packaged item back into a collector's piece, or reusable product, making the package more valuable [5]. The use of ceramic in packaging replaces material like plastic which takes a long time to decompose. Its durability and suitability for reuse conform to sustainable methods, hence the prospect to capture the attention of conscious customers. It is also suggested the use of visual communication comprised of natural colors and green designs or textual messages providing information on its sustainability [6]. Ceramic packaging associates the product with its source by drawing inspiration from the art and tradition of a region. This factor is particularly important in the global market, since exclusive traditional patterns can make products distinct [7].

Creative packaging is gradually gaining acceptance with the new generation of customers. To improve the physical appeal, rough surfaces are used to the packaging, or a design is stamped on the ceramic packaging [8]. Functionality in combination with creativity, like the ability to install storage containers or lids which can be used as cups to enhance the user experience [9]. Ceramic packaging could meet the needs of different consumers due to the integration of modern components in combination with traditional craft. Ceramic art and design can be combined with advanced methods of communicating the art to modern-day customers, such as adding a quick response (QR) code, which contains the history of the product, or an augmented reality (AR) interface [10].

An advanced ceramic packaging design (ACPD) model was created with the use of AI technologies for maintaining the appearance and quality of ceramic materials.

Contributions

➢ The study proposes an AI-driven ACPD model that consists of 3D-CNN, ASVM, and K-Means to design creative and sustainable ceramic packages with superior effectiveness and aesthetics.

➢ The 3D-CNN procedure is employed for precise reconstruction of complex patterns of ceramic containers, thereby enhancing the efficiency of the designs and ensuring the strength and aesthetic appeal.

➢ ASVM is used for classifying and extracting color features from ceramic patterns enabling to develop packaging designs on current trends and customer preferences.

➢ KMC can be used to reveal hidden connections between color and shape, which can be useful for designers when making choices between them.

The study is organized into the following sections: Section 2 - Related Works, Section 3 - Methodology, Section 4 – Result and Discussion, and Section 5 - Conclusion.

RELATED WORKS

Using a computer vision algorithm with DL approaches, research [11] suggested an expanded method for detecting flaws in ceramic components in a manufacturing environment. Through cooperation between the organization and the research group, an intelligent and efficient method for identifying flaws in ceramic pieces was developed, attaining a significant F1 score and accuracy. A screw extrusion 3D printer was used in the investigation [12], to examine the connection between process variables and the strength of deposited lines. Findings from experiments demonstrated the approach's efficacy and applicability. An XGBoost-based forecasting algorithm was created in research [13] to methodically forecast how the compositions, frameworks, and preparation methods of three ceramic substrate materials would affect their flexibility and thermal conductivity. The suggested approach enhanced the development of ceramic materials by reducing the amount of time and expense associated with trial and error in designing and processing. To forecast the flexural durability, Young's modulus, and fracture resistance of UHTCs provided a variety of mixed designs, processing factors, and testing circumstances, research [14] utilized ML approaches. The findings indicated that well-trained ML algorithms could produce a priori forecasts of the three mechanical characteristics.

The use of nonlinear CVs and ML characteristics enables research [15] to achieve *ab initio* reliability MD crystallization predictions of complicated ceramics. The outcome enhanced the study and development of intricate crystalline materials by exhibiting outstanding *ab initio* standards and effectiveness in creating crystallization and producing free energy fields of all the ceramics An ECA process component and an enhanced anchor frame design were used in [16] that proposed a YOLOv5s method to address the issue of tiny target flaw recognition in ceramic plates. The improved YOLOv5s approach exhibited notable gains in F1 scores, mAP, and precision scores. The potential use of ceramic waste in the production of ceramic tiles was examined in the investigation [17]. The findings showed that it was possible to effectively repurpose up to 10% of the waste generated during the ceramic tile production process. An integrated PIML strategy was presented in the research [18] to accurately forecast the creep rupture life of oxide/oxide CMCs by combining microstructure properties and previous physical data. The findings showed that the expected outcomes were always in the ± 3 error range. Essential mechanical characteristics, meso-structural factors, test circumstances, and rupture life were interconnected as an outcome of the methodology.

Using ML approaches to forecast the stoichiometries and characteristics of structures inside a specific layout area, research [19] presented a high-throughput, material-agnostic approach to finding novel compositionally complex ceramics (C^3) for extreme regions. The development of novel architectures and stoichiometries with desirable features was accelerated by the use of ML algorithms, which screen structures with ideal features and lower the computing costs related to property computations. Create ML algorithms for identifying HECCs in the research [20]. Their ML approaches exhibited excellent forecasting accuracy based on the characteristics of HECCs and their predecessors. An ML approach called SVR was used in the research [21] to estimate the TC of SRBSN ceramics based on the process circumstances. When over 100 data points were utilized as the training data, the DC (R^2) in the evaluated outcomes of the trained SVR model achieved an acceptable rate.

ML techniques were used in the research [22] to analyze experimental information for ceramics of the $A_2M_3O_{12}$ family that exhibited NTE. For the linear coefficient of thermal expansion, the resulting models showed forecasting capacity with a DC $R^2 = 0.81$ and a prediction error RMSE = 1.170. An enhanced style transfer method was suggested in research [23] for ceramic product decoration to deal with the uncertainty of intended design impacts and the absence of systematic direction in ceramic painting structure development. The results were extremely important for advancing the growth and history of ceramic painting, decorating art and advancing the creative and cultural sectors.

To automatically create an efficient CNN for the detection and classification of ceranidefect items, research [24] suggested a 2DG-CNN. The other popular strategies were contrasted with the 2DG-CNN. The outcomes demonstrated the effectiveness of the suggested strategy. A DL-based method for detecting defects in ceramic tiles was suggested in research [25]. The detection rate of the proposed approach was significant. As an outcome, it could identify both unknown and known tile properties simultaneously. A lightweight HFENet was suggested in the research [26] for efficient tile surface defect identification. The findings demonstrated that HFENet operated better than lightweight networks and traditional semantic segmentation networks. ResNeXt50 was employed as the basic network in the research [27] in conjunction with the SSD method to obtain multi-scale characteristics of ceramic craft items that had received various surface treatments. Considering recall, precision, and mAP, the research results showed that ResNeXt50-SSD was the most successful for feature identification of ceramic craft items.

Problem statement

Processed ceramics have their drawbacks as packaging materials due to a failure to provide modern requirements for sustainability, cost-effectiveness, and differentiation for consumer usage, with fading aesthetics and designs. Designing geometrically intricate shapes is a problem with the form and function, and existing approaches do not react to market fluctuations. Further, incorporating the color preferences that were customers-oriented into the ceramic packaging design usually proves to be unproductive because it becomes difficult to use colors that can retain their beauty on the packaging while at the same time retaining the hardness needed for the packaging to carry out its function.

METHODOLOGY

The ceramic package design data was gathered. The 3D-CNN approach was utilized for the shape reconstruction, and the color extraction process was done using the ASVM. The KMC approach is used for multivariate statistical analysis. An ACPD-model is developed using the AI-technology. The overall flow of ACPD-model is shown in Figure 1.

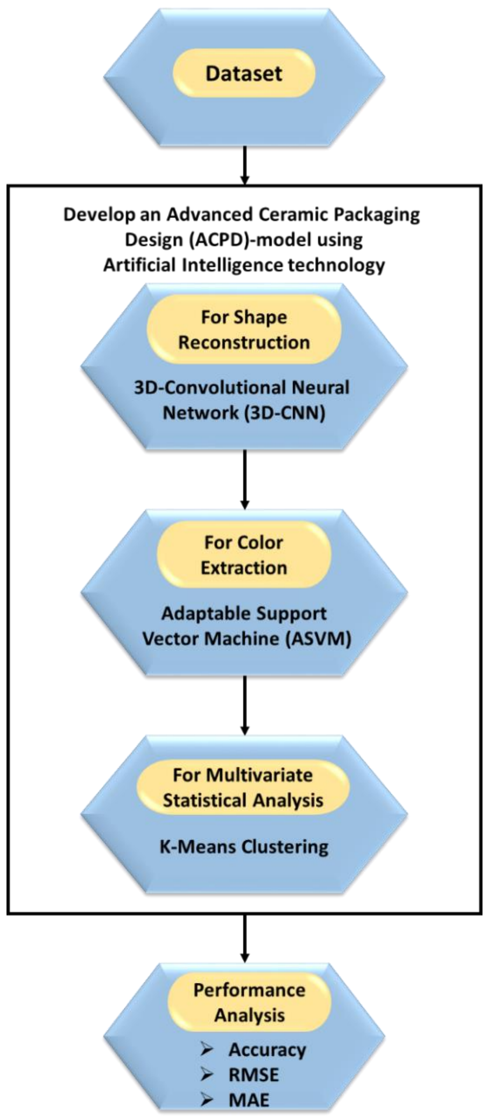

Figure 1: Overview of ACPD-model

Data collection

The ceramic package design data was obtained from the three major sources to ensure a ceramic package design. Visual information that included various shapes, textures, and patterns was obtained by acquiring 500 high-resolution images of the ceramic containers. There were 150 different container designs on which the requirements for dimensions, material kinds, and surface treatment were incorporated. The questionnaires allowed the collection of 200 persons' preferences in terms of colors and shapes. This dataset introduces elements of practice with creative components that can create and enhance packaging, creating an artistic combination between consumers and designers.

3D-CNN for shape reconstruction

The application of 3D-CNNs for shape reconstruction is a prominent strategy for ceramic package design. The problem of prototyping and customization is resolved by the high ability of 3D-CNNs to represent complex shapes and patterns through processing 3D geometric data. These networks can be used to process structural and spatial information and may be able to optimize both functional and aesthetic aspects. Their use enhances accuracy, reduces the possibility of several manufacturing errors, and enables strategists with creative ways of packaging their ceramics that adapt to the numerous customer needs.

3D Convolutional Layer (CL)

When a 3D CL has IS $m \times m \times m$ and c FMs of size $e \times e \times e$, it can be written as $D(m, c, e)$. The result of 3D CL k at point (w, z, y) on the n^{th} FM can be expressed in Equation (1),

$$v_{kn}^{wzy} = a_{kn} + \sum_r \sum_{j=0}^{e-1} \sum_{i=0}^{e-1} \sum_{l=0}^{e-1} x_{knr}^{jil} \, u_{(k-1)r}^{(w+j)(z+i)(u+l)} \quad (1)$$

Where r travels the FMs in the $(k-1)^{th}$ layer, a_{kn} is the FM's bias, and x_{knr}^{jil} is the weight of the kernel of the r^{th} FM at location (j, i, l). The training procedure will produce the bias and the weights.

3D Pooling Layer (PL)

The representation of a 3D PL is $O(m, h)$, which denotes a PL with an IS of $m \times m \times m$ and a pooling kernel of $h \times h \times h$. This method takes advantage of max pooling. On the n^{th} FM of 3D max PL k, the output at location (w, z, y) can be described in Equation (2),

$$v_{kn}^{wzy} = \max_{j,i,l \in \{0,1,\ldots,h-1\}} u_{(k-1)n}^{(hw+j)(gz+i)(hy+l)} \quad (2)$$

Following each pooling layer, the hyperbolic tangent $(tanh(.))$ activation process is employed to enhance nonlinearity.

Network Design

The 2D network's architecture consists of one fully connected layer, two pooling layers, and two CLs. Use the 3D convolutional and 3D pooling layers in place of the 2D convolutional and pooling layers. The framework could be expressed as $D(m_{d1}, c_{d1}, e_{d1}) - O(m_{o1}, h_{o1}) - D(m_{d2}, c_{d2}, e_{d2}) - ED(m_{e1}) - KQ(m_{e2}); ED(m)$.

Where,

$KQ(m)$ - Logistic regression layer with IS m,

$ED(m)$ - Fully-connected layer with IS m.

A final result from softmax that indicates the labeling outcome is an integer $k \in \{0,1,2,..,K\}$. The architecture of 3D-CNN is displayed in Figure 2.

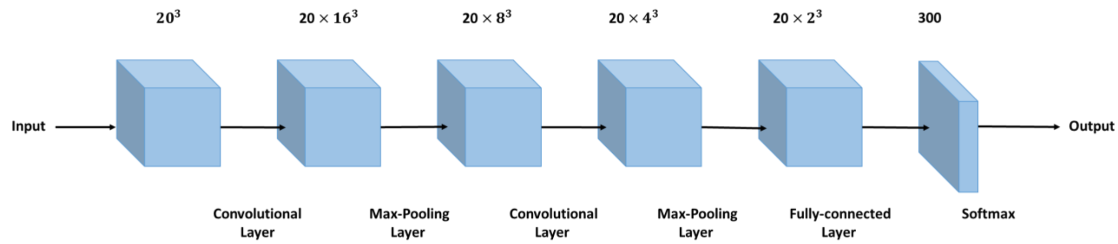

Figure 2: Architecture of 3D-CNN

ASVM for color extraction

The ASVM offers an effective solution for identifying the appropriate colors that should be used in the design of the ceramic package. To accurately recognize and segment complex color patterns, the ASVM alters its parameters. This versatility ensures high performance under different light conditions and ceramic surfaces. ASVM helps to improve the determination of color patterns and enhance the design process. This enables designers to create aesthetically correct packaging, have uniform color-density packaging, and retain accuracy in color reproduction.

The SVM approach operates on the following concept. The categorization issue with m sample-label pairings is given by $T = \left(w_j, z_j\right), (j = 1,2, \dots, m)$, where $z_j \in \{-1, +1\}$ is a class label and $w_j \in Q$ is a training set. The expression $\omega^S w + a = 0$ is used to create a hyperplane to optimize the space between the hyperplane and the support vectors (nearest data points),

Where,

a - Bias factor, and

ω - Vector of hyperplane coefficients.

Utilize the classifier training to identify a hyperplane that can distinguish between the negative (-1) and positive $(+\,1)$ data as shown in Equation (3).

$$\begin{aligned} & min_{\omega,a} \frac{1}{2}\|\omega\|^2 \\ & s.t. \;\; z_j\left(\langle \omega, w_j \rangle + a\right) \geq 1 \end{aligned} \tag{3}$$

An optimization issue must be addressed to determine the ideal separation hyperplane, $\omega^S w + a = 0$.

Finding a hyperplane that can accurately and fully separate data points in some applications is challenging. A complicated categorization hyperplane like this might cause the model to overfit, limiting the forecasting model's generalizability.

A soft margin is employed to overcome the challenge, and the optimization issue is then modified as follows in Equation (3),

$$\begin{aligned} & min_{\omega,a,t} \;\; \frac{1}{2}\|\omega\|^2 + D\sum_{j=1}^{m} \varepsilon_j \\ & s.t. \;\; z_j\left(\langle \omega, w_j \rangle + a\right) \geq 1 - \varepsilon_j, j = 1,2, \dots, m \end{aligned} \tag{4}$$

Where,

D - Penalty coefficient,

ε_j - Slack variable.

However, it is frequently observed that information in real-life operations is non-linearly distinct. The original information should be projected into a high-dimensional area using a nonlinear mapping

Φ_w to address the nonlinearity issue. Linear separability of information may exist in the high-dimensional area.

The Lagrange technique may be used to solve Equations (3 & 4) in dual form. The dual form in a nonlinear instance is expressed in Equation (5),

$$\begin{aligned} &\min_{\alpha} \; \sum_j \alpha_j - \frac{1}{2}\sum_j \sum_i \alpha_j \alpha_i z_j z_i \langle \Phi(w_j) \Phi(w_i) \rangle_E \\ &s.t. \quad 0 \le \alpha_j \le D, \sum_i \alpha_j z_j = 0 \end{aligned} \tag{5}$$

Where the Lagrange multiplier is represented by α_j. The final decision-making function is shown in Equation (6),

$$Class(w) = sign\left(\sum_i \alpha_j z_j \langle \Phi(w_j) \Phi(w) \rangle_E + a\right) \tag{6}$$

The kernel function, which can be written as the inner product $l(w, z) = \langle \Phi(w) \Phi(z) \rangle_E$, is essential to the overall SVM creation process. The kernel determines whether new information and the support vectors are comparable or different. Since the distance between the inputs is a linear conjunction, the dot product is the similarity metric utilized for linear SVM or a linear kernel. A polynomial kernel or a radial basis function kernel is two more kernels that may be utilized for converting the input space into greater dimensions. Pseudo code 1 shows the procedure for color extraction.

Pseudo code: ASVM for color extraction

```
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import numpy as np
import cv2
def extract_color_features(image_path):
image = cv2.imread(image_path)
image_rgb = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
mean_color = np.mean(image_rgb, axis = (0, 1))
return mean_color
def train_asvm_model(features, labels):
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)
X_train, X_test, y_train, y_test = train_test_split(features_scaled, labels, test_size
        = 0.2, random_state = None)
asvm = SVC(kernel = 'rbf', C = 1.0, gamma = 'scale')
asvm.fit(X_train, y_train)
y_pred = asvm.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
```

```
print(f'Model Accuracy: {accuracy * 100:.2f}%')
return asvm, scaler
def predict_color_suitability(model, scaler, color_features):
color_features_scaled = scaler.transform([color_features])
prediction = model.predict(color_features_scaled)
return prediction
if __name__ == "__main__":
image_paths = []
labels = []
color_features = [extract_color_features(image) for image in image_paths]
asvm_model, feature_scaler = train_asvm_model(color_features, labels)
new_image_path = ""
new_color_features = extract_color_features(new_image_path)
suitability = predict_color_suitability(asvm_model, feature_scaler, new_color_features)
print(f"The predicted color suitability for the new image is: {suitability}")
```

KMC for multivariate statistical analysis

KMC is one of the most common multivariate statistical evaluation methods used in the context of ceramic package design to identify patterns and clusters differing from sets of data. It helps designers to better understand customers' preferences and make the right choice of design by classifying any design factors, such as color, texture, shape, and material, into groups based on their similarities. This method is useful in optimizing efficiency in the classification of package design and accurately estimating market trends, hence reducing the costs of production while delivering a unique, improved and successful package design strategy that meets the clients' needs.

A collection of multivariate data's m individuals are divided into K clusters using the KMC technique, where each individual is fully assigned to a single cluster. KMC is repeated as a hard division approach. The first step is to segment the data. The means of each group are determined, and the data is divided once further by assigning every data to the closest means cluster location. This procedure has three steps in its basic form:

Separate the products into the initial K cluster.

Start by grouping the items into clusters based on the nearest centroid (mean). To obtain a new product and for the cluster that missed an object, reevaluate the cluster centroid. The average value, which is established in Equation (7), is used to determine the centroid of the group.

$$D_{li} = \frac{w_{jli}+w_{2li}+\cdots+w_{bli}}{b}, i = 1,2,..,o \tag{7}$$

Where D_{li} represents group-k's centroid, variable-i, and b for the group's member count.

Step (ii) is repeated until the object cannot be transferred.

The distance that is most frequently used is the Euclidean distance. The geometric distance in several spatial dimensions is its most basic form. The raw data, not the standard data, is often used to determine the Euclidean distance. The distance between any two items is unaffected by the addition of extra objects to be examined, which might be an outlier, which is one of the approach's many benefits. The size difference alone can cause the distance to grow significantly. The calculation of Euclidean distance is Equation (8).

$$c(w,z) = \sqrt{(w_1 - z_1)^2 + (w_2 - z_2)^2 + \cdots + (w_o - z_o)^2} \tag{8}$$

Clustering is the process of dividing a given data collection into distinct subsets, or clusters, to maximize particular clustering conditions. The CE criteria, which evaluates the squared distance between every point and the appropriate cluster center and then adds these distances for every point in the information, is the most commonly employed condition. This criterion, which is dependent on the cluster centers, is known as CE. Equation (9) defines the CE.

$$F(n_1, n_2, .., n_l) = \sum_{j=1}^{M} \sum_{l=1}^{L} J\left(w_j \in D_l\right) \left\| w_j - n_l \right\|^2 \tag{9}$$

The mean of cluster D_l is represented by n_l, and $J(W)$ equals 1 if proposition W is true and 0 else.

Several indices are employed to determine the ideal number of groups for the clustering procedure. To find the ideal number of clusters in a collection of data, the Krzanowski and Lai (KL) index measurement is employed. An index that optimizes KL is called optimal K. The KL index calculations are represented by Equations (10 & 11).

$$KL(K) = \left| \frac{DIFF(K)}{DIFF(K+1)} \right| \tag{10}$$

$$DIFF(K) = \left[(K-1)^{2/c} WK_{l-1}\right] - \left[K^{2/c} WK_l\right] \tag{11}$$

WK_k is the shared within-cluster sum of squares of the K divisions, WK_{k-1} is the pooling within-cluster sum of squares of the $K-1$ divisions, and c is the number of sizes of the information.

RESULT

The suggested approach is implemented in Python 3.11 on a Windows 11 laptop with an Intel i7 core CPU and 8GB RAM. The suggested method is evaluated with conventional approaches such as Rhino-based Bi-directional Long Shot Term Memory (BiLSTM) [28] and Rhino-based Support Vector Machine (SVM) [28].

Accuracy and loss

The validity of an ACPD model is the ratio of the number of correct predictions that have been stated by the model to the total number of forecasts that have been made by the same model. It shows the capability of the model to accurately describe the attributes or responses of ceramic materials based on computed and actual values. The discrepancy between the actual target values and the output that the ACPD model predicts is measured using a metric called loss. It functions as an indicator of error; a larger loss denotes a larger departure from the actual values. The model training is to reduce loss gradually to increase the model's accuracy and performance. The output of accuracy and loss is displayed in Figure 3.

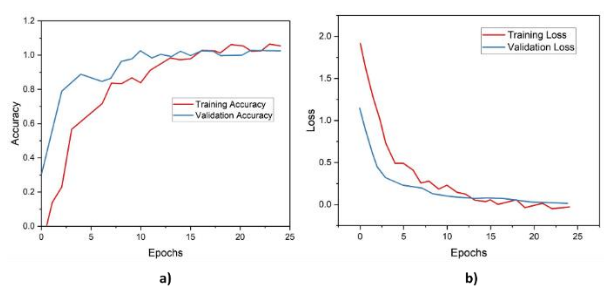

Figure 3: Output of a) accuracy and b) loss

Smarter Ceramic Packaging Design

The smarter ceramic packaging designs important performance metrics are shown in Figure 4. The color classification earned 89.5% in terms of reflecting market trends, and its 94.7% accuracy ensured accurate agreement with consumer preferences is displayed in Figure 4 (a). In terms of sustainability, 85% recyclability score indicates a dedication to ecologically friendly techniques, while the 96% material utilization rate shows the effective use of resources is displayed in Figure 4 (b). By optimizing production time by 20% and improving structural durability by 50%, the design streamlines the manufacturing process is displayed in Figure 4 (c). These numbers demonstrate how AI-driven optimization affects design and manufacturing, striking a balance between sustainability, usability, and aesthetics.

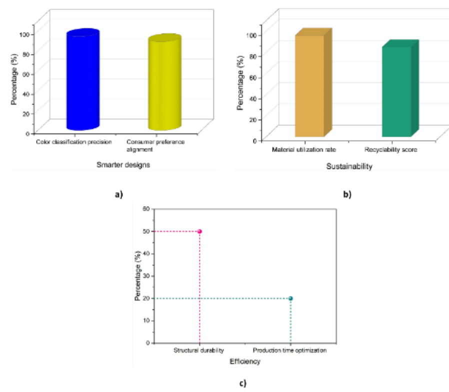

Figure 4: Result of Smarter Ceramic Packaging Design

Accuracy

Accuracy is the extent to which the predictions, simulations, or outcomes of the ACPD model are close to the actual measurements or standards. To ensure the realistic representation of the packing system under operating conditions, it is necessary to ensure the accuracy of the variables regulating the mechanical characteristics, electrical conductivity, temperature regulation, ceramic components, and reliability of the packing system. To maximize design efficiency and dependability for sophisticated applications, accuracy necessitates combining accurate material data, and sophisticated computational methods. In comparison with the traditional Rhino-based BiLSTM and Rhino-based SVM approaches, the suggested ACPD-model has an accuracy value of 95.41%, whereas the traditional Rhino-based BiLSTM and Rhino-based SVM approaches have accuracy values of 93.71% and 87.52%, as displayed in Figure 5.

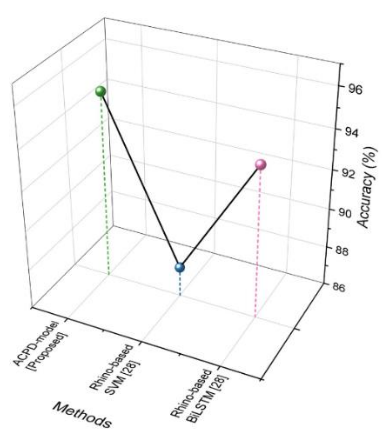

Figure 5: Result of accuracy

RMSE

The performance of such forecasting tools, including the development of an ACPD-model, is generally assessed by evaluating the RMSE statistic. RMSE is calculated from the SR of the average of the squared difference in the actual and the anticipated values. As RMSE values decrease, they provide a quantity of how well the model performs by reducing the prediction error of the model. In the context of ACPD, RMSE could be used for the determination of the accuracy of the model with which it is possible to predict variables, such as mechanical strength, thermal conductivity, or failure rates of the ceramic material in different conditions, ensuring that the design complies with performance criteria. When compared to the suggested ACPD-model, the conventional Rhino-based BiLSTM and Rhino-based SVM approaches have high RMSE values of 0.241 and 0.274, whereas the suggested ACPD-model has an RMSE value of 0.223, respectively. The result of RMSE values is displayed in Figure 6.

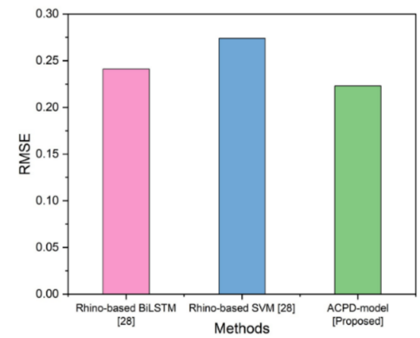

Figure 6: Output of RMSE

MAE

The ACPD-model is also formulated based on the Mean Absolute Error (MAE), which is one of the most important statistics used to evaluate a prediction model's performance. The model's prediction errors are simply determined by using the formula of mean absolute deviation of the discrepancies between the PV and AV. Through the establishment of the size of prediction errors, MAE supports the assessment of how well a model identifies significant aspects such as electrical resistance, mechanical strength, or thermal conductivity from the perspective of ACPD. The model with the lower MAE is considered a more accurate one and it is important to note that it is necessary to achieve the highest dependability and performance of advanced ceramic packing materials for technologies with a high density of electronics or other advanced technologies. The traditional Rhino-based BiLSTM and Rhino-based SVM techniques have high MAE values of 0.10 and 0.126 when compared to the suggested ACPD-model, whereas the suggested ACPD-model has an MAE value of 0.06, as displayed in Figure 7. Table 1 shows the overall result comparison.

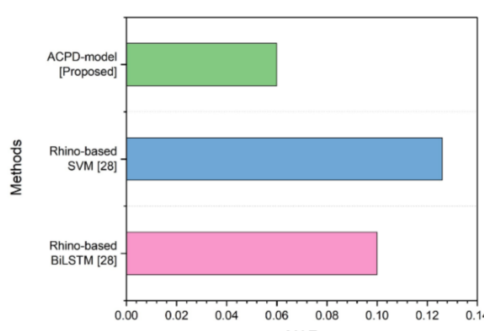

Figure 7: Result of MAE

Table 1: Result comparison

Methods	RMSE	MAE	Accuracy%
Rhino based BiLSTM [28]	0.241	0.10	93.71%
Rhino based SVM[28]	0.274	0.126	87.52%
ACPD-Model [Proposed]	0.223	0.06	95.41%

DISCUSSION

Rhino-based BiLSTM can handle sequential data with the help of forward and backward information; it could be challenging for this model to capture the truly non-linear complex features of the advanced ceramic packaging design that involves material properties, thermal and mechanical behaviors. Furthermore, the demonstrated model could need a large amount of computation and large-scale training data to learn non redundant variability across different design conditions, resulting in overfitting or suboptimal approximation of the best design solutions. Rhino-based SVM is not good at handling high-dimensional problems, a problem frequently encountered in most engineering designs, where over-fitting or under-fitting is likely to occur if the feature space is large and data sparse. In addition, Rhino-based SVM was found not to be directly suitable for handling noisy or unstructured data that can be included in material and manufacturing process characteristics and can hinder its implementation in real-world construction. SVM is sensitive to its hyper parameters and the regularization parameter, which takes plenty of computation time and resources to optimize. To overcome these challenges, the research presents APCD-model using AI technology to maintain the quality and aesthetic features of ceramic materials.

CONCLUSION

Ceramic packaging design creates the most durable and creative packaging materials by combining the aesthetic appeal and functionality of packaging ideas. The ceramic packaging design data was collected. Advanced ceramic package design results from the integration of AI technologies, such as 3D-CNNs, ASVM, and KMC, combining traditional artistry with current computing efficiency. Advanced ceramic package design improved from the integration of AI technologies, such as 3D-CNNs, ASVM, and KMC, combining traditional artistry with modern computing efficiency. The ACPD-model explains how AI can maintain the quality of the aesthetic and physical features of ceramic materials while improving design functionality, efficiency, and sustainability. The performance of the ACPD-model is evaluated in terms of accuracy (95.41%), RMSE (0.223), and MAE (0.06). The possible challenge of precisely capturing subjective visual perceptions in automated systems is one of the study's limitations. To improve design customization and innovation in ceramic packaging, future studies should investigate a more thorough integration of AI-driven user experience suggestions.

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APPENDIX

PIML	Physics-informed machine learning	UHTC	Ultrahigh temperature ceramics
3D	Three dimensional	ECA	Efficient Channel Attention
ML	Machine learning	CMC	Ceramic matrix composites
IS	Input size	SVM	Support Vector Machine
SVR	Support vector regression	SRBSN	Sintered reaction-bonded silicon nitride
MD	Molecular dynamics	DL	Deep learning
HECC	High-entropy ceramic carbides	NTE	Negative thermal expansion
CNN	Convolutional neural network	CE	Clustering error
HFENet	Hand-crafted feature enhanced convolutional neural network	CL	Convolutional layer
CV	Collective variable	mAP	Mean average precision
TC	Thermal conductivity	PL	Pooling layer
XGBoost	Extreme boosting	DC	Determination coefficient

SSD	Single Shot MultiBox Detector	2DG-CNN	Two-dimensional genetic algorithm-based convolutional neural network
FM	Feature map	AV	Actual values
PV	Predicted values	SR	Square root