Metaverse Basic and Applied Research. 2025; 4:216
doi: 10.56294/mr2025216

ORIGINAL

Research on Computer Vision Teaching of Mongolian Silver Jewelry Making Techniques

Investigación sobre la enseñanza de la visión por ordenador en las técnicas mongolas de fabricación de joyas de plata

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Cite as: Jun X, Sukhbayar B. Research on Computer Vision Teaching of Mongolian Silver Jewelry Making Techniques. Metaverse Basic and Applied Research. 2025; 4:216. https://doi.org/10.56294/mr2025216

Submitted: 18-06-2025 **Revised:** 26-08-2025 **Accepted:** 25-10-2025 **Published:** 26-10-2025

Editor: PhD. Dra. Yailen Martínez Jiménez

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ABSTRACT

Introduction: jewelry making is an integral part of Mongolian craftsmanship, reflecting the country's rich cultural heritage and artistic traditions. However, traditional methods often lack mechanisms for real-time feedback, limiting learner's ability to detect and correct production defects. To address this issue, this research introduces computer vision-based teaching framework that integrates Deep learning (DL) for analyzing handcrafted silver jewelry, enhancing learning outcomes and preserving traditional artistry.
Method: the research utilizes the open-source Mongolian Silver Jewelry Defect Dataset (MSJDD) from Kaggle, comprising 1050 samples of handcrafted jewelry. A Scalable Transient Search-tuned Multi-Cascaded Convolutional Neural Network (STS-MCCNN) model was developed to classify jewelry pieces, identify surface defects, and evaluate craftsmanship quality. The dataset was preprocessed using Min-max scaling to reduce noise, while Principal Component Analysis (PCA) was applied to improve feature extraction. The AI-driven interface enables users to input jewelry characteristics, receive automatic defect analysis, and visualize analytical heat maps highlighting critical defect zones, supported by an adaptive feedback mechanism for skill refinement.
Results: experimental evaluations revealed that the proposed STS-MCCNN model achieved 98,5 % accuracy, 98,36 % recall, and 98,25 % F1-score, supporting its high reliability in defect detection and craftsmanship evaluation. Moreover, the integration of real-time feedback significantly improved learner engagement and precision in jewelry-making techniques.
Conclusions: this research demonstrates how combining traditional artistry with AI technologies can preserve and modernize Mongolian jewelry-making practices. The proposed STS-MCCNN method enhances both learning and cultural continuity, offering a sustainable pathway for advancing artisan education and safeguarding intangible cultural heritage.

Keywords: Mongolian Silver Jewelry; Defect Detection; Computer Vision; Making Technology; Interactive Interface; Scalable Transient Search-tuned Multi-Cascaded Convolutional Neural Network (STS-MCCNN).

RESUMEN

Introducción: la elaboración de joyas es un componente esencial del trabajo artesanal de Mongolia, el cual representa las ricas tradiciones artísticas y la herencia cultural del país. No obstante, los métodos tradicionales a menudo carecen de mecanismos para la retroalimentación en tiempo real, lo que restringe el potencial del alumno de identificar y corregir defectos de producción. Para abordar este problema, esta investigación presenta un marco de enseñanza basado en visión computarizada que incorpora el aprendizaje

profundo (DL) para analizar joyería de plata hecha a mano, mejorar los resultados del aprendizaje y mantener la maestría tradicional.
Método: la investigación emplea el conjunto de datos de defectos de joyería en plata mongola (MSJDD) disponible en Kaggle, que está compuesto por 1050 muestras de joyería hecha a mano. Con el fin de categorizar piezas de joyería, detectar fallas en la superficie y analizar la calidad de la manufactura, se creó un modelo llamado Scalable Transient Search-tuned Multi-Cascaded Convolutional Neural Network (STS-MCCNN). Para disminuir el ruido, se utilizó Min-max scaling para preprocesar el conjunto de datos; al mismo tiempo, con el fin de optimizar la extracción de características, se empleó el Análisis de Componentes Principales (PCA). La interfaz impulsada por inteligencia artificial permite a los usuarios introducir características de la joyería, obtener un análisis automático de defectos y visualizar mapas térmicos analíticos que señalan zonas críticas de defectos, respaldados por un mecanismo de retroalimentación adaptativa para perfeccionar sus habilidades.
Resultados: las evaluaciones experimentales mostraron que el modelo STS-MCCNN propuesto logró un 98,5 % de precisión, un 98,36 % de sensibilidad y un 98,25 % de F1-score, lo que respalda su elevada fiabilidad en la detección de fallos y la evaluación de la calidad de la fabricación. Además, el uso de retroalimentación en tiempo real aumentó considerablemente la precisión y el compromiso del aprendiz en las técnicas de fabricación de joyas.
Conclusiones: este estudio muestra cómo la combinación de las artesanías tradicionales con las tecnologías de inteligencia artificial puede mantener y modernizar los métodos de fabricación de joyas en Mongolia. El método STS-MCCNN propuesto mejora la continuidad cultural y el aprendizaje, brindando una vía sostenible para promover la educación de los artesanos y proteger el patrimonio cultural inmaterial.

Palabras clave: Mongolian Silver Jewelry; Defect Detection; Computer Vision; Making Technology; Interactive Interface; Scalable Transient Search-tuned Multi-Cascaded Convolutional Neural Network (STS-MCCNN).

INTRODUCTION

Several popular methods are used in jewelry manufacturing, including die-struck, machine-made, and casting operations. Craftspeople, workers, specialized equipment, and drawn-out production procedures are needed for these procedures. Typically, mass manufacturing is used to create several identical jewelry items in factory-manufactured jewelry.(1) Consequently, handcrafted jewelry is more distinctive and appealing than machine-made jewelry, its demand is increasing. An alternate material for making handcrafted jewelry is precious metal clay, which can be used to make artwork, miniature sculptures, and ornamental items.(2) Humanity is entering an era of knowledge explosion and rapid scientific and technological advancement due to the quick growth of the global economy and culture. Through a range of media, including music and images, different information sources can influence people's senses. Art has progressively become more ingrained in people's lives in contemporary society, where production has significantly increased.(3)

The utility of items is no longer enough for modern consumers, who have new aesthetic and ideological demands. As seen by the abundance of gold and silver jewelry businesses and stores, metal jewelry is utilized to satisfy the expressive and religious requirements of the majority of people.(4) Making jewelry is a social activity that promotes interaction and community development. In jewelry-making workshops or groups, senior citizens can encourage one another, discuss methods, and experience the bond that comes with creating together.(5) Their reciprocal impact and traction can produce works with a higher level of modern machine production and more manual processing technology.(6)

The production of semi conductive Coordination Polymers (CPs) utilizing trithiocyanuric acid (H3ttc) with infinite Ag-S bond networks was optimized using Machine Learning (ML).(7) Following the publication of three CP crystal structures, it was demonstrated that the main factor influencing isomer selectivity was the proton content in the reaction medium. Multilayer perceptron neural networks to smooth the time series and analyze the content.(8) The findings demonstrated that silver can maintain its worth not just when investors stop using cash to build wealth for both people and businesses.

Traditionally, computationally demanding Density Functional Theory (DFT) was used to forecast energy values across a catalyst surface.(9) To identify the best sites for adsorbed chlorine in the ethylene epoxidation reaction, a unique DL method is suggested for creating an exhaustive energy map. The ability of various DL systems to forecast silver prices was assessed.(10) The prediction process using DL models, including Convolutional Neural Network (CNN), Long-Short-Term Memory (LSTM), and Gated recurrent unit (GRU), as well as a new hybrid model that combined these models. The CNN-LSTM-GRU hybrid model might be able to generate more accurate forecasts, which assessed the performance of numerous DL algorithms for predicting silver prices using historical data.

With an emphasis on producing realistic jewelry images, it compares five more popular AI algorithms to investigate how generative AI created the designs in response to text and image suggestions. The ethical, legal, and regulatory issues that have emerged about AI-generated art were addressed.[11] The Egyptian civilization saw several distinct stages in the production of handicrafts. Silver has been in Egypt since ancient times and has experienced multiple periods of scarcity. Although there was disagreement about whether silver originated in Egypt, Egyptian artisans' proficiency with this rare metal cannot be denied.[12]

The use of synthetic materials was growing in popularity and presented fresh opportunities from an inventive and creative standpoint. The jewelry design practice presented a fresh and difficult setting that should offer a more constructive and long-lasting method.[13] The research was to outline potential futures for sustainable jewelry materials by fusing design and science. The use and importance of Inner Mongolian traditional art elements in the context of contemporary oil painting education and pedagogy are examined.[14] The core elements of the nomadic culture that was common in the northern steppe region were embodied in Inner Mongolia's traditional artistic characteristics.

To provide a thorough understanding of how gender roles emerge, are negotiated, and are maintained within the unique sociocultural context of the Van Gujjar group, the main goal was to examine the beliefs, ideas, and collective perspectives that shape these craftswomen's life.[15] By analyzing the principles, ideas, and group viewpoints that direct these craftswomen's lives. The Genetic Algorithm (GA)-based research optimization approach was used to automatically modify and optimize jewelry design scenarios.[16] The experiment involved selecting various jewelry cases with different types and design specifications, utilizing both research optimization procedures and conventional design techniques. Jewelry manufacturing has developed from traditional handcrafted procedures to current machine-assisted and AI-driven technologies that reflect both cultural history and technology advancement. Handcrafted silver jewelry is still highly regarded for its distinctiveness, although artists frequently face difficulties in detecting faults and increasing quality efficiently. Existing approaches rarely provide learners with real-time feedback, which limits skill improvement. The research aims to develop a model that leverages Scalable Transient Search-tuned Multi-Cascaded Convolutional Neural Network (STS-MCCNN) to classify jewelry pieces, identify surface defects, and assess craftsmanship quality.

METHOD

The suggested approach starts with a collection of silver jewelry designs from Mongolia. A Min-max normalization is used in data preprocessing to improve quality and lower noise. The PCA is used for feature extraction to record crucial structural information. To ensure precise and effective examination of Mongolian silver jewelry, the STS-MCCNN is finally used to categorize jewelry pieces, identify surface flaws, and evaluate craftsmanship quality. Figure 1 demonstrates the structure of the suggested STS-MCCNN method.

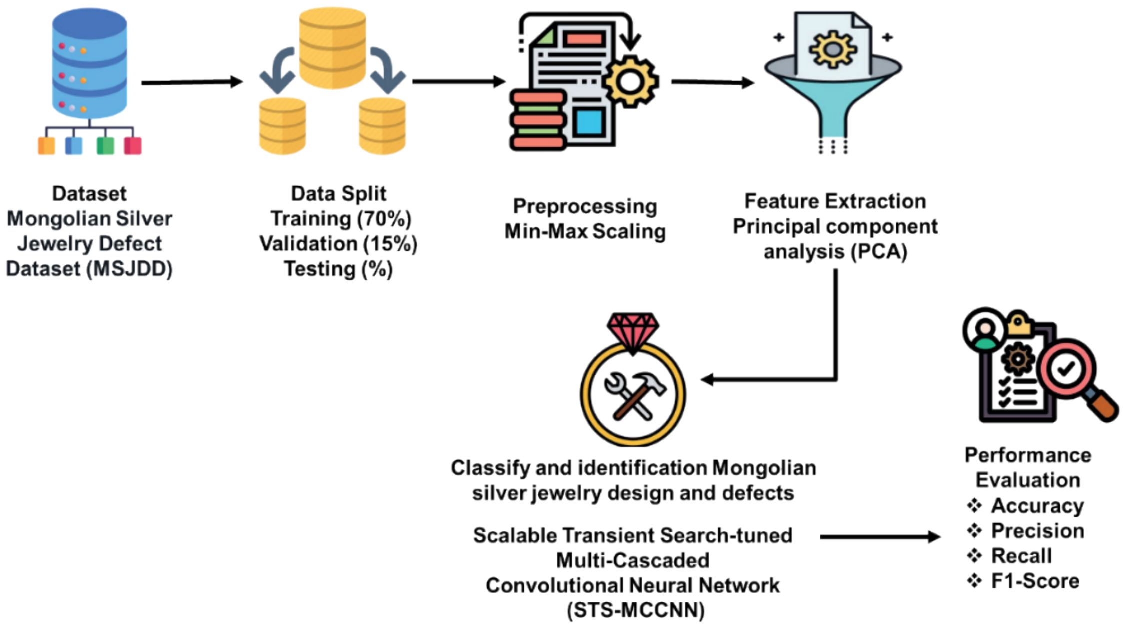

Figure 1. System model flow in the suggested STS-MCCNN approach

The purpose of the Mongolian Silver Jewelry Defect Dataset (MSJDD) is to identify flaws in handcrafted Mongolian silver jewelry gathered from the open-source platform Kaggle.[17] Labeled data reflecting various jewelry attributes and flaws, such as scratches, cracks, and normal (defect-free) pieces, are included. The goal of the dataset is to train deep learning (DL) models specifically, computer vision-based quality evaluation systems that will help craftspeople spot flaws and enhance their work via AI-powered feedback in a total sample of 1050. The data splits the training set 70 % (750 samples), the validation set 15 % (150 samples), and the testing set 15 % (150 samples). A crack indicates structural flaws with substantial surface damage. Scratch displays the superficial flaws that detract from attractiveness. Normal displays jewelry that is of excellent quality and free of obvious flaws. Table 1 shows the overall dataset feature attributes.

Table 1. Feature attributes in the dataset[17]

Feature Attribute	Description
Surface Roughness	Measures unevenness on the jewelry surface.
Color Intensity	Represents the polish and shine level of silver.
Engraving Depth	Depth measurement of artistic carvings.
Structural Integrity	Overall stability and strength of the jewelry piece.
Defect Size	The proportion of the jewelry surface affected by visible defects.

Preprocessing using Min-max scaling

The original data is standardized to ensure that the indicators are the same size to facilitate comprehensive comparison and assessment in detecting silver jewelry design. The outcomes are scaled from 0 to 1 because of outlier normalization and a linear modification of the initial information. Data with values that are substantially close to one another perform effectively. The transformation function employed in the min-max scaling is equation (1).

$$y' = \frac{y - y\ (\text{min})}{y\ (\text{max}) - \text{y}\ (\text{min})} \qquad (1)$$

Where, y (max) symbolizes every sample data's greatest value, y' presents the normalized value of y, rescaled between 0 and 1, y demonstrates the original value before normalization, and y (min) symbolizes the sample data's lowest value.

Extraction feature using principal component analysis (PCA)

The variance information is preserved as features are extracted from the original data, PCA is a feature extraction technique that lowers the dimensionality of data in classifying and detecting handcrafted silver jewelry. Dimensionality reduction reduces the impact of duplicate information in upcoming feature learning and allows for the conversion of several data characteristics into a small number of data attributes without significantly sacrificing critical information. Moreover, computational efficiency is increased by lowering the number of model parameters due to the reduction in input characteristics in classifying and detecting jewelry pieces. The following are PCA's primary stages. To prevent certain larger data points from producing significant mistakes, the standardization procedure brings all data points' sizes into the same range. The following is the standardizing equation (2).

$$W_{new} = \frac{W_j - \mu}{\sigma} \qquad (2)$$

Where, Wj is the original feature value, μ is the mean of all feature values, σ is the standard deviation, and Wnew is the standardized feature.

The covariance matrix of the data points is computed to determine the correlation between the data points. Following equation (3) is the covariance matrix, Con_{MN} denotes covariance between feature Nand feature M.

$$Cov = \begin{bmatrix} Con_{11} & Con_{12} & \cdots & Con_{1N} \\ Con_{21} & Con_{22} & \cdots & Con_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ Con_{N1} & Con_{N2} & \cdots & Con_{MN} \end{bmatrix} \qquad (3)$$

The primary components of the data are found by computing the covariance matrix's eigenvalues and the related eigenvectors of the classify jewelry pieces approach. To create a vector matrix, feature vectors are ordered in rows from top to bottom based on the magnitude of feature values; the higher the order, the lower the relevance.

https://doi.org/10.56294/mr2025216 **ISSN:** 2953-4577

Defect identification using Scalable Transient Search-tuned Multi-Cascaded Convolutional Neural Network (STS-MCCNN)

The STS-MCCNN capacity to process vast amounts of data quickly and accurately makes it a defect identification approach. The STS-MCCNN combines transient search optimization with a multi-cascaded CNN framework. The hybrid model enhances defect identification by improving layer connectivity, and optimizes the identification of defects in complex datasets.

Multi-Cascaded Convolutional Neural Network (MCCNN)

To increase accuracy, a deep learning (DL) model called an MCCNN processes visual data through several consecutive CNN stages for defect detection in handcrafted Mongolian silver jewelry. By concentrating on many facets of the jewelry's characteristics, the MCCNN improves its predictions at every level for jewelry classification, defect identification, and craftsmanship quality evaluation. Where, $X \in R^{h \times w \times c}$ denotes the input jewelry design with height h, width w, and c represents the color channels. The MCCNN extracts features through cascaded convolutional layers. Where Wl and Fl denotes convolutional filters at layer l, bl is the bias, and σ represents the non-linear activation function (equation 4).

$$F_l = \sigma(W_l * X + b_l),\ l = 1,2,\dots,L \qquad (4)$$

The jewelry type is classified by a final softmax layer, where N is the number of jewelry types. Regression analysis is used to forecast the craftsmanship quality score Q∈[0,10], with the mean squared error (MSE) loss, as follows equations (5-6). Where, Qi presents the true score Q ̃i denotes the predicted score.

$$Q = W_q^T F + b_q \qquad (5)$$

$$\mathcal{L}_{quality} = \frac{1}{m}\sum_{i=1}^{m}\left(Q_i - \hat{Q}_i\right)^2 \qquad (6)$$

Equation (7) shows that the weighted sum represents the total loss function for MCCNN.

$$\mathcal{L} = \lambda_1\mathcal{L}_{class} + \lambda_2\mathcal{L}_{class} + \lambda_3\mathcal{L}_{quality} \qquad (7)$$

Where λ_1, λ_2, and λ_3 balance the contributions of each task. The cascaded design ensures high accuracy in automated jewelry analysis by effectively refining jewelry classification, flaw diagnosis, and craftsmanship rating.

Scalable Transient Search (STS)

The population intelligence algorithm's accuracy and convergence speed can be greatly impacted by the initial population's diversity in jewelry defect detection. However, the basic STS is prone to randomly initializing the population, which results in poor-quality populations and reduces the algorithm's merit-seeking accuracy and convergence speed. Chaotic mapping fully extracts and captures the synthetic data in a solution space to provide high-quality starting populations. One of the most popular detection methods in chaos theory research is logistic chaos mapping, which employs the following mathematics iteration using Equation (8) as a representation mechanism.

$$\lambda_{s+1} = \mu \times \lambda_s(1 - \lambda_s), s = 0,1,2,\dots,S \qquad (8)$$

Where S denotes the predefined extreme number of chaotic iterations, is a chaotic control parameter, and λs denotes the circulated evenly haphazard value in the interval [0,1] that involves.

The assignment variables for every d-dimensional search agent are then sequentially mapped onto the higher and smaller bounds of the target position using each chaotic sequence and the generated set of chaotic elements λ in equation (9).

$$W_j^i = ka + \lambda_i \times (va - ka) \qquad (9)$$

Where Wj irepresents the coordinate of the ith search agent's jth dimension, and λi represents the coordinate of λ dimension following internal random ordering.

The possibility of superior investigators on the opposite side of the search area is undeniable, even though chaotic sequences can produce categories that are diverse and widely distributed in silver jewelry detection, consequently, equation (10) yields an equal number of opposing populations.

$$W_{op_j} = W_{max} + W_{min} - W_j \quad (10)$$

Where the positions of the j^{th} agent's opposing position (x), the greatest boundary's position (Wmax), the smallest boundary's position (Wmin), and the j^{th} individual's position (Wj) are all represented. When these are finally combined, 2N different search agent groups are produced, with {W, Wop } as the population. The beginning populations are selected from the N groups with the greatest fitness after the condition of the different populations is assessed.

Adaptive Weights for Inertia: the inertia weights of the initial STS algorithm are fixed, which limits the system's ability to find value and the rate of convergence. Lower inertia weights can speed up convergence and improve local fine-looking performance in the late iteration, whereas larger inertia weights can enhance the worldwide exploration capability in the primary iteration. Every STS search process relies on the inertia weighting approach chosen in classifying and detecting jewelry; hence the following equation suggests a method for adaptively varying the inertia weights based on the number of repetitions.

$$x(s) = b\ cos^{a}\left(In\left(1 + f^{\frac{s}{Smax}}\right) + d\right) \quad (11)$$

The parameters a, b, and dare optional. Numerous tests were conducted until it was determined that the optimal values for a, b, and d were 21, 15, and 0,4, etc. Equations (11-13), which use the following mathematical formulas, govern how the exploration and exploitation actions of STS are distributed when adaptive inertia weights are introduced.

$$W(s+1) = x(s).W*(s) + f^{-S}[\cos(2\pi S) + \sin(2\pi S)]|W(s) - D_1 W*(s)| \quad (12)$$
$$W(s+1) = x(s).W*(s) + [W(s) - D_1.W*(s)].f^{-S} \quad (13)$$

Each scalability of Mongolian silver jewelry detection guarantees strong performance in a variety of applications, including time-series forecasting. In the real-world, data-intensive scenarios where efficiency and dependability are essential for the strongest possible decision-making, STS-MCCNN is perfect, since it lowers computational complexity while retaining high predicted accuracy. Algorithm 1 illustrates the suggested STS-MCCNN method.

Algorithm: STS-MCCNN

```
class MCCNN:
   def __init__(self, layers, num_classes):
self.layers = layers
self.num_classes = num_classes
   def forward(self, X):
      F = X
      for layer in self.layers:
         F = layer.forward(F)
      return F
   def classify(self, F):
      return softmax (F)
   def compute_loss (self, X, y):
      F = self.forward(X)
      P = self.classify(F)
L_class = -sum(y_i * log(P[y_i]) for y_i in range (self.num_classes))
      Q = self.regress_quality (F)
L_quality = mean_squared_error (Q, y)
      L = λ1 * L_class + λ2 * L_class + λ3 * L_quality
      return L
   def regress_quality (self, F):
      return W_q.T * F + b_q
```

```
class STS:
   def chaotic_map(self, λ_s):
      return chaotic_param * λ_s * (1 - λ_s)
   def search(self, agents, bounds):
      λ = [random.uniform (0, 1) for _ in range (len(agents))]
      W = self.map_onto_bounds(agents, λ, bounds)
      for _ in range(max_iterations):
         λ = [self.chaotic_map (λ_s) for λ_s in λ]
W_op = [self.opposing_position(W_j) for W_j in W]
         agents = [self.update_position(agent, W_j, bounds) for agent, W_j in zip(agents, W_op)]
      return agents
   def map_onto_bounds(self, agents, λ, bounds):
      return [[bounds[d][0] + λ_i * (bounds[d][1] - bounds[d][0]) for d, λ_i in enumerate(λ_i)] for λ_i in λ]
   def opposing_position(self, W_j):
W_max = max(W_j)
W_min = min(W_j)
      return [W_max + W_min - W_ij for W_ij in W_j]
   def update_position(self, agent, W_j, bounds):
      return [max(min(W_ij, bounds[d][1]), bounds[d][0]) for d, W_ij in enumerate(W_j)]
def train_mccnn_with_sts(X_train, y_train, num_epochs, batch_size):
mccnn = MCCNN(layers=initialize_layers(), num_classes=10)
sts = STS()
   for epoch in range(num_epochs):
      for batch in create_batches(X_train, y_train, batch_size):
X_batch, y_batch = batch
         agents = initialize_search_agents(X_batch, y_batch)
optimized_agents = sts.search(agents, bounds=[(0, 1)] * len(X_batch))
         for agent in optimized_agents:
            loss = mccnn.compute_loss(X_batch, y_batch)
         print(f"Epoch {epoch}, Loss: {loss}")
   return mccnn
```

RESULTS

System configuration: the Intel (R) Core (TM) i3 Lenovo platform, which has a main CPU speed of 3 GHz and 8 B of memory, is used to experimentally classify Mongolian silver jewelry detection. Python is used in the development of the suggested system.

Accuracy: accuracy is a widely used metric in classifying and detection jewelry piece applications. A model calculates the proportion of accurate forecasts among all the classifications and detections it makes. The following equation (14) is used to determine it.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (14)$$

Precision: equation (15) calculates the precision of positive forecasts by calculating the percentage of expected positive values that are positive. A performance metric called precision calculates the proportion of accurate predictions among all positive predictions.

$$Precision = \frac{TP}{TP+FP} \quad (15)$$

Recall: the percentage of correct positive guesses among all of a dataset's actual positive values is determined by the prediction performance indicator in detection and classify handcrafted jewelry. Equation (16) is used to assess the model's capacity to distinguish positive instances from every positive occurrence.

$$Recall = \frac{TP}{TP+FN} \quad (16)$$

F1-score: an objective evaluation of the model's effectiveness is provided by the F1 score, which is calculated as a harmonic average of precision and recall. Equation (17) demonstrates that this metric takes into account the model precision and recall, which makes it particularly useful when the dataset's distribution of positive and negative classes is not uniform.

$$F1 - score = \frac{2 \times precision \times recall}{Precision + recall} \quad (17)$$

Note: true negative (TN), true positive (TP), false positive (FP), and false negative (FN).

Dataset splitting outcome: the training validation, test data sets were randomly selected from the data collection in a 70:15:15 ratio. Table 2 displays the preparation of experimental data.

Table 2. Outcome of the experimental data

Category	Train	Validation	Test	Total
Scratch	400	50	50	500
Normal	200	25	25	250
Crack	240	30	30	300
Total	840	105	105	1050

Contrasting the Performance: the comparative analysis evaluates the STS-MCCNN method against existing methods for improved convolutional neural network (CNN)[18] for Mongolian silver jewelry detection with evaluation metrics, such as precision, accuracy, recall, and F1-score in 30-60 epochs.

The representation of (a) precision, (b) recall, and (c) F1 score in detection and classify handcrafted jewelry is illustrates in table 3 and figure 2. The proposed STS-MCCNN method achieves high performance, such as a precision of 98,5 %, recall of 98,36 %, and F1-score of 98,25 %, slightly outperforming the improved CNN (98,3 % precision, 98,2 % recall, 98 % F1-score) in defect detection accuracy.

Table 3. Overall numerical outcomes precision, recall, and F1-score

Method	Precision (%)	Recall (%)	F1-score (%)
Improved CNN[18]	98,3	98,2	98
STS-MCCNN [Proposed]	98,5	98,36	98,25

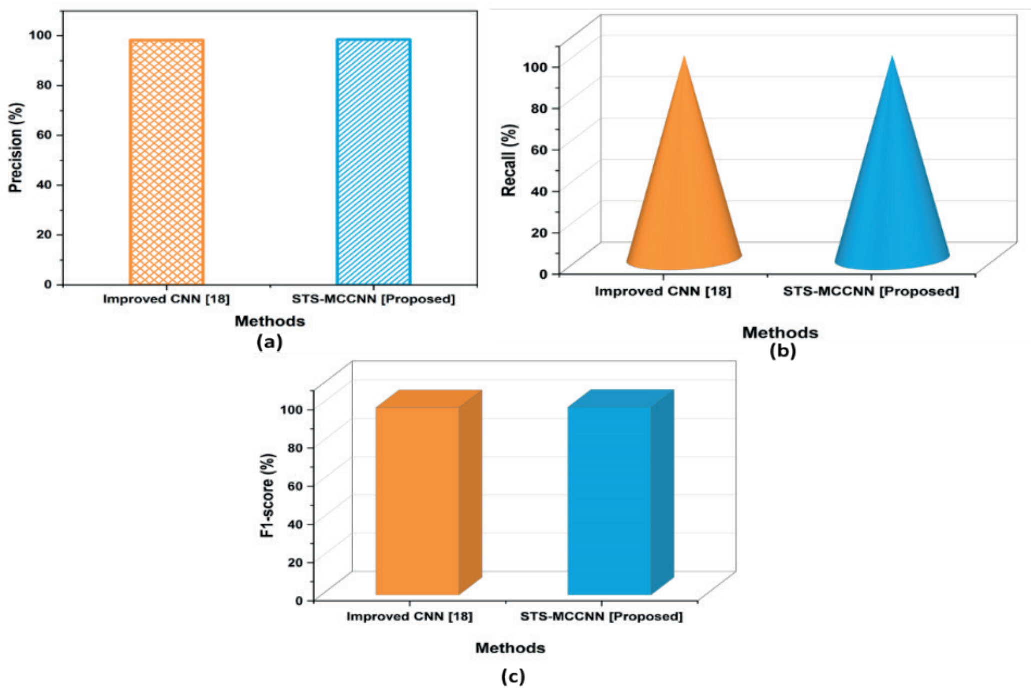

Figure 2. Graphical representation of the (a) precision, (b) recall, and (c) F1 score

Table 4 and figure 3 display the outcomes of the accuracy based on the epochs. The proposed method achieved higher accuracy (98,3 %) compared to improved CNN (97,3 %) at 60th epoch.

Table 4. Outcomes of the accuracy in existing, and suggested method

	Accuracy (%)	
Epoch	Improved CNN[18]	STS-MCCNN [Proposed]
30	96,1	96,8
40	97,3	97,7
50	97,9	98
60	97,3	98,3

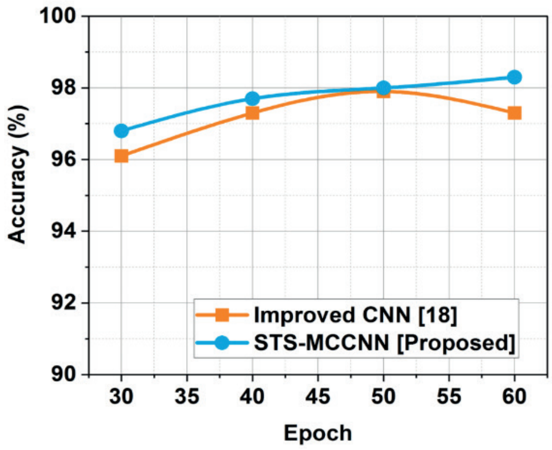

Figure 3. Comparison experiment for accuracy

DISCUSSION

The integration of DL technology into Mongolia's jewelry-making education represents a pivotal advancement in preserving and enhancing traditional craftsmanship. The exploratory character of this research, which employs scenario analysis rather than empirical testing, limits the direct validation of practical outcomes in jewelry design, even while it highlights creative applications of sustainable materials.(13) Lacking a more comprehensive sociolinguistic framework, empirical support, and a quantitative comparison of Mongolian and Korean cultural interpretations, the research is constrained by its concentration on metaphorical expressions from specific linguistic sources.(14) The research findings are restricted by its small and context-specific sample size, reliance on qualitative ethnographic interpretation, and absence of a broader comparative or quantitative analysis to generalize gender role dynamics across the community.(15) The algorithm face constraints in the intricate artistic interpretations, inadequate training data diversity, real-time performance scalability, and generalization to unconventional or highly customized jewelry designs.(16) First involved dataset partitioning in a 70:15:15 ratio for training, validation, and testing, ensuring balanced representation across defect categories such as scratch, normal, and crack. Second phase analyzed comparative performance between the improved CNN and the proposed STS-MCCNN model. Results demonstrated superior precision (98,5 %), recall (98,36 %), and F1-score (98,25 %) for STS-MCCNN, confirming its improved classification robustness. Third phase examined accuracy over 30–60 epochs, where STS-MCCNN achieved 98,3 % accuracy at the 60th epoch, outperforming the improved CNN (97,3 %). To address the limitations of conventional and improved CNNs, which exhibit constrained feature extraction capacity and slower convergence when processing small, texture-rich datasets such as handcrafted jewelry images.(18) The suggested STS-MCCNN method through transient search-based parameter tuning and multi-cascaded convolutional layers, which enhance adaptive learning and hierarchical feature representation. It is achieves faster convergence, higher defect detection accuracy, and improved interpretability for real-time jewelry evaluation.

Limitation and Future scope: the system confronts difficulties in integrating complicated AI technology, generating significant manufacturing and deployment costs, and adapting to elaborate designs. Adaptation for various individual body types and style demands is also difficult. Future research should concentrate on refining the AI model for cost-effectiveness, broadening its application to more complex forms, and enabling wider use across artisan groups.

CONCLUSIONS

Computer vision techniques can improve Mongolian silver jewelry-making education by combining traditional artistry with AI-driven analysis. The research addresses the challenges in providing real-time feedback for flaw detection, which is often lacking in traditional training methods. The research effectively analyzed and categorized surface faults using the MSJD dataset from Kaggle, which included 1,050 handcrafted jewelry products. Preprocessing was carried out using Min-max scaling to normalize feature values and remove noise, followed by PCA to extract features and reduce dimensionality. The suggested STS-MCCNN method was created to automatically detect faults, assess workmanship quality, and generate heat maps that indicate key defect regions. The addition of real-time feedback to the AI interface increased learner precision and engagement, demonstrating the method's efficacy in advancing ability development and preserving Mongolian jewelry-making traditions.

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FINANCING
No financing.

CONFLICT OF INTEREST
The authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION
Formal analysis: Xi Jun.
Research: Xi Jun.
Project management: Battsooj Sukhbayar.
Software: Xi Jun.
Supervision: Battsooj Sukhbayar.
Drafting - original draft: Xi Jun.
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