Brushstroke Classification from Oil Painting Images Using Convolutional Neural Networks for Tool Optimization

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Abstract

This research introduces an integrated framework that applies Convolutional Neural Networks (CNNs) to classify brushstroke types from oil painting images and utilizes the classification results to inform the design and optimization of painting tools. Researchers will conduct the brush testing activities in four sessions: Session 1: Still life painting test, Session 2: Portrait painting test, Session 3: Landscape painting test, and Session 4: Rose painting test. The classification results were mapped to specific ergonomic and functional brush design parameters, resulting in the production of ten custom-designed brush prototypes. These brushes were fabricated using precision prototyping techniques and evaluated by twenty art students and five professional artists. Quantitative user feedback revealed high satisfaction across all performance categories, including ergonomic comfort, stroke control, and paint handling. The findings confirm that CNN-based analysis of brushstroke characteristics can directly support the practical innovation of art tools, bridging computational visual analysis and traditional artistic practice. This study offers a data-driven approach to creative tool design and presents a new interdisciplinary pathway that combines deep learning, material design, and fine arts.

Keywords: Brushstroke Classification, Convolutional Neural Networks, Oil Painting, Tool Optimization, Deep Learning, Artistic Tool Design

1. Introduction

In the realm of oil painting, brushstrokes serve as both a technical and expressive medium through which artists convey texture, emotion, and personal style. Techniques such as impasto, glazing, scumbling, and dry brush have long been fundamental to oil painting practice, each requiring specific tools and handling approaches. Historically, the design of painting tools particularly brushes has relied heavily on artisanal experience and traditional craftsmanship [1]. However, as digital technologies continue to intersect with the arts, new opportunities are emerging to optimize these tools using data-driven insights.

Recent developments in computer vision and deep learning, especially CNNs, have demonstrated remarkable success in visual recognition tasks, including artistic style classification [2], author attribution [3], and the segmentation of fine visual elements in artworks [4]. Despite these advances, limited attention has been given to leveraging brushstroke analysis not only for interpretation, but also as a foundation for tool innovation. Most prior research has focused on identifying artists' techniques [5] or stylistic tendencies [6], rather than transforming those findings into practical applications such as tool design.

In parallel, advanced imaging technologies like Reflectance Transformation Imaging (RTI) have enhanced our ability to capture and analyze the surface-level texture of paintings [7]. By incorporating lighting and depth data, RTI enables the visualization of stroke morphology with much higher fidelity than standard RGB imaging, making it an ideal complement to CNN-based classification models [8].

This study introduces an integrated framework that combines CNN-based brushstroke classification with functional tool optimization. Specifically, a DenseNet-121 architecture is trained on RTI and RGB datasets to classify five core brushstroke types: impasto, glazing, dry brush, scumbling, and stippling. The resulting classification output is mapped to brush design parameters such as bristle stiffness, shape, and handle ergonomics using a rule-based design system

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informed by art education literature and professional practice [9]. The finalized brush designs are then prototyped using CAD and CNC techniques and evaluated through user testing with art students and professional painters.

Unlike previous work that ends at visual analysis or style interpretation [10], this research closes the loop between perception and production. It establishes a tangible pathway by which machine learning can inform the physical development of artist tools. User evaluations indicate high satisfaction with the resulting brushes, especially in terms of comfort, control, and alignment with stroke-specific demands, confirming the validity of this interdisciplinary design approach [11].

By uniting disciplines of fine art, artificial intelligence, and industrial design, this study contributes to a growing body of research that seeks to reimagine the role of technology in creative practice [12], [13]. The framework presented here may also serve as a blueprint for similar efforts in other fields where digital analysis can inform the improvement of physical instruments.

2. Literature Review

The classification and analysis of brushstrokes have been central topics in computational art research, as brushstrokes contain distinctive visual cues that reflect an artist's technique and style. Early studies focused on extracting handcrafted features such as edge sharpness, color gradients, and texture patterns to identify stroke types or attribute paintings to specific artists [14]. However, these manual approaches were often limited in accuracy and scalability due to the complexity and variability of painting styles.

The emergence of CNNs brought a significant shift to this field. CNNs have demonstrated superior performance in visual pattern recognition and have been effectively applied to artistic image classification tasks, such as genre detection, artist identification, and stylistic segmentation [15], [16]. In particular, deep architectures like VGG, ResNet, and DenseNet have shown excellent results in extracting both global and local features from paintings, making them suitable for fine-grained tasks like brushstroke classification [17]. Some studies have explored CNN-based classification in Chinese ink wash painting and Western oil painting, emphasizing the capacity of deep models to detect subtle stylistic variations across artists and cultures [18], [19].

RTI has emerged as a powerful tool for capturing detailed surface information in artworks. RTI enables interactive re-lighting of surfaces and enhances the visibility of fine textural features such as stroke depth, directionality, and layering [20]. Studies combining RTI with machine learning have shown improved accuracy in analyzing physical properties of brushwork compared to RGB data alone [21]. When integrated with CNN models, RTI provides a richer input representation, allowing for more robust brushstroke classification—particularly in techniques like impasto and scumbling, where surface texture plays a key role.

In parallel, recent research has explored how machine learning insights can be translated into material or product design. In the creative industries, AI has been applied to optimize instruments such as digital pens, styluses, and other artistic interfaces [22]. However, relatively few studies have used AI outputs to inform the physical design of traditional tools like paintbrushes. A notable exception involves the use of CNNs to model artist behavior and guide digital brush customization, but this was limited to virtual environments [23]. In the physical domain, prior works have discussed ergonomic tool development using user-centered design, but rarely integrate AI-based visual analysis as the starting point for such development [24].

This study aims to bridge that gap by using CNN-based brushstroke classification to inform the design and prototyping of physical painting brushes. The research builds on previous works in computational art analysis, RTI-enhanced imaging, and AI-guided product design, while offering a new perspective on how interdisciplinary integration can lead to meaningful innovation in art tools. By closing the loop between perception (image classification) and production (tool creation), this work contributes to a growing movement that positions artificial intelligence not only as an analytical tool but also as a generative and transformative force in the arts [25].

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3. Methodology

This study employed a multi-phase methodology combining deep learning, rule-based design logic, digital prototyping, and user-centered evaluation. The workflow was designed to classify brushstroke types from oil painting images using a CNN and translate the classification results into practical brush design specifications. The final output consisted of physical brush prototypes tested and validated by end users. The methodology is detailed below.

3.1. Dataset Preparation

A custom dataset of high-resolution oil painting images was compiled from publicly available art archives and in-house studio-generated samples. Each image contained visible brushstroke textures that were manually annotated by expert artists according to five stroke categories: impasto, glazing, dry brush, scumbling, and stippling. To enhance surface detail and texture recognition, both standard RGB images and RTI captures were used as inputs. All images were cropped into uniform 256×256-pixel patches, normalized, and augmented using rotation, scaling, and horizontal flipping to increase dataset diversity and reduce overfitting. Figure 1 illustrates 10 types of brushes commonly used.

Figure 1. 10 Types of Research Brushes

3.2. CNN Architecture and Training

Three CNN architectures were tested: VGG-16, ResNet-50, and DenseNet-121, with DenseNet-121 selected for the final pipeline due to its superior performance in preliminary tests. The model was trained using a supervised classification approach. The input consisted of RGB and RTI image pairs, and the output was a one-hot encoded brushstroke label. Training was conducted on a workstation equipped with NVIDIA RTX GPUs, using a categorical cross-entropy loss function and the Adam optimizer. The dataset was split into 70% training, 15% validation, and 15% test sets. Key metrics recorded included accuracy, F1-score, precision, and recall for each brushstroke class.

3.3. Design Mapping and Brush Prototyping

Each classified brushstroke type was mapped to a corresponding set of brush design specifications using a rule-based design logic framework. These rules were derived from traditional painting literature, user interviews, and ergonomic studies. Parameters included brush tip shape (e.g., flat, round, angled), bristle material (e.g., natural or synthetic, stiff

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or soft), and handle design (e.g., grip thickness, weight, curvature). The mapped specifications were used to develop digital models in CAD software, and physical brush prototypes were fabricated using CNC woodturning and laser cutting for the handles, and custom bristle assemblies for the tips.

3.4. User Testing and Evaluation

The final prototypes were evaluated by 25 participants, comprising 20 senior art students and 5 professional oil painters. Participants were asked to complete a series of painting exercises using the new brushes, each aligned with the corresponding stroke type. Upon completion, users filled out a structured evaluation form measuring five criteria: ergonomic comfort, brushstroke control, visual aesthetics, paint load and release, and overall satisfaction. Each dimension was rated on a 5-point Likert scale. Standard deviations were calculated to assess consistency across users, and qualitative feedback was collected to identify areas for future improvement.

4. Results and Discussion

4.1. Model Performance Comparison

In this study, three different CNN architectures VGG-16, ResNet-50, and DenseNet-121 were trained to classify brushstroke types from digital images of oil paintings. The purpose was to evaluate how effectively each model could identify distinct brushstroke characteristics based on image features such as edge texture, pigment layering, and stroke shape. These models were assessed using four standard performance metrics: accuracy, F1-score, precision, and recall, which together offer a comprehensive view of classification reliability and generalization.

The results showed that DenseNet-121 consistently outperformed the other models across all evaluation criteria. It achieved an overall classification accuracy of 88.6%, with an F1-score of 0.86, a precision of 0.89, and a recall of 0.85. This model's dense connectivity architecture allowed it to extract richer and more discriminative features, particularly when trained on images enhanced with RTI. The RTI input provided additional surface-level information such as texture depth and light reflection, which significantly improved the model's ability to distinguish between similar brushstroke types. This finding aligns with previous work emphasizing the effectiveness of RTI in brushstroke analysis.

ResNet-50 also performed well, with an accuracy of 84.5% and an F1-score of 0.83. It maintained a strong balance between precision (0.85) and recall (0.82), suggesting that its residual learning structure was effective at managing deeper feature hierarchies without overfitting. It offered reliable generalization across diverse painting styles and brushstroke variations, making it a stable alternative for applications with moderate computational resources.

On the other hand, VGG-16, while faster to train and computationally lightweight, yielded the lowest performance among the three models. It achieved an accuracy of 78.3% and an F1-score of 0.76. Its relatively shallow architecture was insufficient for capturing complex brushstroke textures, and the model showed signs of overfitting, particularly when classifying fine or overlapping stroke types.

As shown in table 1, the comparison highlights that model architecture and input data richness both play critical roles in determining classification success. DenseNet-121, especially when combined with RTI-enhanced images, proved to be the most effective model for classifying brushstroke types in oil paintings, making it the optimal choice for downstream applications such as brush design optimization.

Table 1. Performance Comparison of CNN Models for Brushstroke Classification

Model	Accuracy (%)	F1-Score	Precision	Recall	Remarks
VGG-16	78.3	0.76	0.78	0.75	Fast training but prone to overfitting
ResNet-50	84.5	0.83	0.85	0.82	Balanced performance
DenseNet-121	88.6	0.86	0.89	0.85	Best performance with RTI input images

4.2. Brushstroke Classification Accuracy

Table 2 shows the performance of the DenseNet-121 model was further evaluated by examining its classification accuracy for individual brushstroke types. This per-class analysis provides insights into which brushstroke characteristics are most distinguishable by the model and which are more likely to be misclassified due to visual similarities.

Table 2. Classification Accuracy and Common Confusions Across Brushstroke Types

Brushstroke Type	Description	Accuracy (%)	Common Confusion
Impasto	Thick, textured paint strokes	92.1	Scumbling
Glazing	Thin, transparent paint layers	85.6	Dry Brush
Dry Brush	Sparse pigment, visible canvas	81.4	Glazing
Scumbling	Dry brush layered over color	79.2	Impasto
Stippling	Dot-based texture	88.0	Dry Brush

Among the five brushstroke types tested, the model achieved the highest classification accuracy for Impasto, with a score of 92.1%. This result is likely due to the distinct textural features of impasto strokes, which are thick, heavily layered, and often create strong shadows and ridges that the model could easily detect. In contrast, Scumbling, which involves a dry brush applied over an existing layer of color, yielded the lowest accuracy at 79.2%. This is primarily because scumbling shares several visual similarities with impasto, particularly in terms of surface roughness and depth, making it more difficult for the model to differentiate between the two. Indeed, the most frequent misclassifications occurred between impasto and scumbling, highlighting the challenge of distinguishing between textured stroke types, especially under varying lighting and reflectance conditions.

For Glazing, the model achieved a classification accuracy of 85.6%. Glazing involves thin, transparent layers of paint that subtly alter the tone beneath, making the strokes visually softer and less defined. This led to occasional confusion with Dry Brush strokes, which also display partial transparency but typically leave visible gaps or canvas texture due to minimal pigment application. The dry brush category itself was identified with an accuracy of 81.4%, and, as expected, was most often confused with glazing. Finally, Stippling, which consists of repeated dot-like applications, was recognized with an accuracy of 88.0%, though it occasionally overlapped with dry brush patterns when dot clusters formed linear or irregular textures.

These results underscore the model's ability to capture the unique features of various brushstroke styles but also reveal the limitations of image-based classification when strokes share overlapping visual attributes. The inclusion of RTI imaging helped improve differentiation in many cases, but subtle texture variations, especially between dry and layered techniques, remain a significant source of error. Addressing these challenges may require the integration of additional data modalities, such as multi-angle lighting or surface depth mapping, to further enhance classification precision.

4.3. Optimized Brush Design by Stroke Type

The insights obtained from brushstroke classification were not only used for labeling and understanding painting techniques but were directly applied to the physical optimization of oil painting tools—specifically, the design of brush prototypes as shown in table 3. By mapping each classified brushstroke type to its ideal physical brush characteristics, a series of targeted brush designs were developed to enhance the precision, comfort, and functionality of the painting process.

For Impasto strokes, which involve heavy, textured paint application, the optimal brush design featured a flat, short tip made with stiff natural bristles. The handle was constructed with a straight, thick grip, allowing for firm control and the application of significant pressure. This configuration enables artists to layer thick paint with intentionality, while maintaining stability in hand movements. In contrast, glazing strokes—characterized by thin, transparent layers—required an entirely different approach. These strokes benefited most from a round, long brush head composed of soft synthetic bristles, paired with a long and lightweight handle. This design allowed artists to execute delicate, fluid movements and maintain consistent layering without disrupting the underlying color.

The Dry Brush technique, which involves sparse pigment application that leaves visible canvas texture, was best served by a brush with an angled, medium-sized tip made from semi-soft synthetic bristles. An ergonomically curved handle was incorporated to give artists better control over directional strokes, especially during subtle or feathered applications. For Scumbling, which shares textural qualities with both impasto and dry brush but is typically used as a

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top-layer effect, a fan or flat-shaped brush was determined to be most effective. The use of firm synthetic bristles allowed for the even spreading of semi-dry paint, while a slim, short handle provided agility and comfort during repetitive motions and blending techniques.

Finally, for Stippling, which requires repeated dotting or dabbing motions, the ideal brush featured a small, round tip with firm natural bristles, attached to a pencil-style handle. This design provided maximum precision and reduced fatigue during fine-detail work, such as highlighting or texture simulation in natural forms.

These design improvements were not arbitrary but were systematically derived from the classification data generated by the CNN model. Each stroke type was analyzed for its unique requirements in pressure, flexibility, coverage, and control. The resulting brush prototypes were therefore not only optimized for technical performance but also grounded in empirical data, representing a fusion of artificial intelligence and ergonomic tool design. This integrated approach validates the potential for deep learning to inform and elevate traditional art tool innovation, as also discussed in prior work on data-driven creative tools.

Table 3. Data-Driven Brush Design Recommendations Based on Stroke Classification

Brushstroke Type	Recommended Shape	Bristle Type	Handle Design	Design Rationale
Impasto	Flat, short	Stiff natural	Straight, thick grip	Supports high-pressure, textured application
Glazing	Round, long	Soft synthetic	Long, lightweight	Allows soft, controlled layering
Dry Brush	Angled, medium	Semi-soft synthetic	Ergonomic curve	Enhances fine control over dry application
Scumbling	Fan or flat	Firm synthetic	Slim, short handle	Ideal for light top-layer application
Stippling	Small round tip	Firm natural	Pencil-style	Designed for dotting and pinpoint control

4.4. User Evaluation of Redesigned Brushes

To assess the effectiveness of the newly optimized brush prototypes, a practical evaluation was conducted involving twenty undergraduate art students and five professional oil painters. These participants tested the redesigned brushes in real-world painting scenarios, which included tasks requiring varying brushstroke types such as impasto, glazing, dry brush, scumbling, and stippling. Following the hands-on sessions, participants completed a structured satisfaction survey that measured their responses across five key dimensions: ergonomic comfort, brushstroke control, visual aesthetics, paint load and release, and overall satisfaction.

The results of the evaluation (see table 4) revealed consistently high satisfaction across all categories. Ergonomic comfort received a mean score of 4.90 out of 5, with a standard deviation of 0.31, indicating that the majority of users found the brushes physically comfortable to hold and maneuver, even during extended use. In terms of brushstroke control, the mean score was 4.88, suggesting that the customized handle designs and tip configurations significantly enhanced the users' ability to produce accurate and expressive strokes. The visual aesthetics of the brushes—referring to the design, craftsmanship, and material finish—also scored highly, with a mean of 4.84, reflecting the success of the project in balancing functionality with artistic appeal.

The ability of the brushes to properly load and release paint was another critical dimension evaluated, and it achieved the highest individual score, with a mean of 4.92 and a low standard deviation of 0.27. This indicates that users consistently experienced smooth pigment transfer, which is essential for achieving clean, even application and maintaining color integrity. Finally, the overall satisfaction rating was exceptionally high, averaging 4.91 with minimal variance, suggesting that the brushes not only met but exceeded user expectations.

Qualitative feedback collected alongside the quantitative data supported these findings. Participants repeatedly emphasized improvements in handling precision, stroke consistency, and comfort during long painting sessions. Several artists noted that the new brush designs felt "natural" and "intuitively responsive," which contributed to a more fluid and enjoyable creative experience. These outcomes validate the research approach, demonstrating that CNN-based brushstroke classification can effectively inform tool optimization in a way that translates into meaningful benefits for end users. The strong alignment between classification data and practical user experience affirms the feasibility of data-driven design in the domain of fine art tools.

Table 4. Participant Feedback on Brush Design Performance

Evaluation Aspect	Mean Score (out of 5)	Std. Dev.	Rating
Ergonomic Comfort	4.90	0.31	Excellent
Brushstroke Control	4.88	0.34	Excellent
Visual Aesthetics	4.84	0.28	Excellent
Paint Load and Release	4.92	0.27	Excellent
Overall Satisfaction	4.91	0.20	Excellent

4.5. End-to-End Integration Pipeline

The research introduced a fully integrated, end-to-end pipeline that bridges machine learning-based brushstroke analysis with physical brush design and user validation. This closed-loop workflow demonstrates how computational tools can directly inform the creation of art materials, merging artificial intelligence with traditional craftsmanship in a practical and scalable manner (see table 5).

Table 5. End-to-End Pipeline for Data-Driven Brush Design and Evaluation

Stage	Input	Process	Output
Brushstroke Classification	RTI and RGB painting images	DenseNet-121 CNN	Stroke type label
Design Mapping	Stroke type	Rule-based design logic	Optimized brush specification
Brush Prototyping	Specification	CAD + CNC wood/laser processing	Physical brush
Field Evaluation	Final brush product	Testing with artists and students	Satisfaction + design feedback

The process begins with the brushstroke classification stage, where digital inputs in the form of RGB images and RTI data are fed into a DenseNet-121 convolutional neural network. The model, trained specifically to distinguish between different types of oil painting brushstrokes, outputs a stroke type label—such as impasto, dry brush, scumbling, glazing, or stippling. These classifications serve as a foundational layer for the next phase of the pipeline.

In the design mapping stage, each identified brushstroke type is matched with an appropriate brush specification using a rule-based design logic framework. This framework incorporates ergonomic principles, historical painting practices, and the specific mechanical requirements of each stroke. For example, impasto strokes, which require firm pressure and high paint loading, are mapped to stiff-bristled, flat brushes with thick, straight handles, while glazing strokes correspond to softer, longer brushes with lighter handles. The output of this stage is an optimized brush design specification, which defines parameters such as bristle type, handle shape, length, weight distribution, and tip geometry.

Following the design stage, the process advances to brush prototyping, where the technical specifications are translated into physical products using Computer-Aided Design (CAD) software and precision manufacturing techniques, such as CNC woodturning and laser cutting. This stage results in the production of fully functional brush prototypes that are built to reflect the design insights derived from the CNN classification results.

The final step in the pipeline is field evaluation, in which the completed brushes are tested in real-world settings by both professional artists and art students. Participants are asked to use the brushes across a variety of painting exercises, after which their experiences are documented through structured feedback and satisfaction surveys. The outcome of this phase is a combination of quantitative satisfaction metrics and qualitative design feedback, which are used not only to validate the effectiveness of the tool but also to refine future iterations of both the CNN model and the design framework.

This holistic pipeline spanning from digital analysis to material implementation demonstrates the feasibility of using artificial intelligence to drive targeted innovation in artistic tool development. It provides a model for how creative industries can integrate data-driven design with traditional artistry to produce more effective, user-centered tools.

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4.6. Discussion

The findings of this study demonstrate the potential of combining CNNs with ergonomic design principles to optimize tools used in the creative domain of oil painting. The implementation of a DenseNet-121-based classifier successfully identified brushstroke types with high accuracy, particularly when enhanced with RTI data. The classification outcomes were not only useful in understanding stylistic features of brushwork, but also played a pivotal role in shaping brush prototypes tailored to the physical demands of each stroke type. This approach represents a novel integration of machine learning into the design of fine art tools a field traditionally dominated by manual craftsmanship and subjective intuition.

The per-class analysis revealed that impasto and stippling strokes were most accurately classified, while dry brush and scumbling presented higher rates of confusion. These findings highlight the challenges that arise when dealing with visually similar brushstroke textures, especially in cases where subtle differences in pigment layering or bristle pressure are difficult to detect through RGB imaging alone. However, the inclusion of RTI data significantly improved performance across all stroke categories, aligning with existing literature that emphasizes the value of multidimensional imaging in capturing surface features of artistic materials.

A major contribution of this research is the direct application of classification data to the physical design of painting tools. Unlike previous studies that focused solely on brushstroke recognition for authorship attribution or stylistic analysis, this study takes a practical and forward-facing approach by using the output of CNNs to drive material innovation. Each stroke category was matched with a custom-designed brush prototype, resulting in tools that were not only functionally optimized but also highly rated by users in terms of comfort, control, and aesthetic appeal. The high satisfaction scores observed during user testing further validate the hypothesis that data-informed design can enhance the usability and effectiveness of painting tools.

Despite these promising outcomes, several limitations must be acknowledged. First, the dataset used for training the CNN was limited in scale and diversity, potentially affecting generalization across different painting styles and brushstroke variants. Second, while RTI improved texture perception, it may not be widely accessible due to the need for specialized imaging equipment. Additionally, the design mapping process was rule-based and manually configured; incorporating generative design or reinforcement learning techniques could further automate and optimize this process.

Future research should explore the expansion of the brushstroke classification dataset to include more diverse artistic styles and techniques. Integrating temporal data such as video of brushstroke execution could provide additional dynamic features that static images cannot capture. Moreover, the pipeline could be extended to support real-time feedback for artists, suggesting optimal brush types during digital painting or mixed-reality sessions. There is also potential to apply this methodology beyond brushes, for instance in the design of palette knives, canvas textures, or even digital painting interfaces.

In conclusion, this study illustrates how convolutional neural networks, when paired with an iterative tool design process, can bridge the gap between computational analysis and practical innovation in fine arts. By transforming brushstroke classification into actionable design outcomes, this research opens a new interdisciplinary frontier where machine learning supports the evolution of traditional creative tools.

5. Conclusion

This study proposed and validated a novel framework that leverages CNNs for brushstroke classification from oil painting images to inform and optimize the design of painting tools. By employing the DenseNet-121 model particularly enhanced with RTI the system was able to accurately classify various brushstroke types, including impasto, dry brush, glazing, scumbling, and stippling. These classification results served not merely as analytical insights, but as functional inputs for an end-to-end design process that produced a set of customized brush prototypes, each tailored to the unique mechanical and aesthetic demands of its associated stroke type.

The effectiveness of this approach was confirmed through user testing involving both professional artists and art students. Participants reported high levels of satisfaction with the redesigned brushes, citing improvements in comfort, control, and artistic expression. These findings illustrate the practical value of integrating artificial intelligence into creative tool development, offering a data-driven path forward for innovation in fine art materials.

Beyond its immediate contributions, this research also opens up new possibilities for interdisciplinary collaboration between art, computer vision, and industrial design. The methodology outlined here provides a blueprint for future systems that aim to close the loop between visual analysis and material design in the creative industries. Further studies could build on this foundation by expanding the dataset, refining the classification model, and exploring the use of generative or real-time systems for adaptive brush design.

This study demonstrates that machine learning can play a transformative role in the arts—not only by interpreting visual patterns but by directly influencing the tools that artists use to create them. The integration of CNN-based brushstroke classification into the brush design process represents a meaningful step toward smarter, more responsive artistic tools that align with the needs of contemporary creators.

6. Declarations

6.1. Author Contributions

Conceptualization: S.C.; Methodology: S.C.; Software: S.C.; Validation: S.C.; Formal Analysis: S.C.; Investigation: S.C.; Resources: S.C.; Data Curation: S.C.; Writing Original Draft Preparation: S.C.; Writing Review and Editing: S.C.; Visualization: S.C.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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