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Optimized RE-CNN-Based Multi-Objective Decision Framework for Visual Feature Evaluation in Computational Art Analysis and Interactive Media

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ABSTRACT

Recent developments in digital art preservation have facilitated the integration of deep learning algorithms into decision-support systems by means of computational methodologies. This study proposes a hybrid approach employing the Zebra Optimisation Algorithm to enhance the performance of Random Ensemble-based Convolutional Neural Network (RE-CNN) models for the assessment of industrial product designs. By translating aesthetic evaluations, emotional responses, and memorability ratings provided by human reviewers into quantifiable insights, the model generates valuable operational guidance for visual media in the context of mechanical engineering design processes. Enhanced predictive capabilities are achieved through the optimisation of RE-CNN parameters, allowing for more accurate analysis of diverse product aesthetics. The advisory system presented offers design engineers and product developers a perceptual image generation tool tailored to achieving specific design goals. Product image evaluation is conducted by human assessors utilising systems that integrate decision-tree methodologies with content analysis protocols, enabling the interpretation of colour properties alongside visual elements. The system contributes to automated design decision-making by offering data-informed support for product selection within commercial environments. The adopted research methodologies contribute to the optimisation of mechanical systems and user interfaces, ensuring that visual and emotional design considerations remain paramount. Within artificial intelligence frameworks, engineers are thus able to create specialised products while accelerating the development of mechanical design systems.

1. Introduction

Artificial intelligence (AI) and deep learning methods derived from computational intelligence

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exert significant influence on mechanical engineering design, particularly in relation to manufacturing and optimisation processes [4]. Engineers benefit from the integration of generative algorithms and machine learning technologies, which facilitate the enhancement of mechanical system development by improving process management, material precision, and design accuracy [18]. By adopting AI-driven methodologies, engineers are able to devise advanced manufacturing systems and innovative design approaches that support the implementation of novel techniques in mechanical engineering design activities [12; 13].

In professional practice, mechanical engineers increasingly rely on real-time optimisation enabled by deep learning models as a fundamental aspect of their operational expertise. These professionals can utilise automated systems to process extensive design datasets, thereby influencing the selection of materials and the configuration of product structural components [7]. The incorporation of deep learning-based optimisation within generative algorithms leads to improved workflow performance, particularly within computer-aided design (CAD) and computer-aided manufacturing (CAM) environments [20]. The deployment of such automated systems allows engineers to allocate greater attention to strategic, high-level tasks, resulting in markedly improved product specifications compared to conventional engineering methodologies. Furthermore, AI technologies contribute to reduced time-to-market by continuously incorporating customer feedback to iteratively refine prototypes in real-time development cycles.

A notable domain where AI has demonstrated considerable impact within manufacturing is material science [17]. Machine learning systems process performance data from diverse operational scenarios and material contexts through advanced analytical techniques. Accurate prediction of material properties is critical for the identification of sustainable and functional materials [15]. The application of the Zebra Optimisation Algorithm (ZOA) within RE-CNN frameworks improves the predictive precision of material performance. As a result, mechanical design managers benefit from greater flexibility in material selection, as the system accommodates a broad range of design requirements without imposing limiting constraints.

Historically, mechanical engineering design has often overlooked aesthetic evaluation; however, AI now plays a transformative role in this domain [15]. Products with high visual appeal tend to achieve greater success in competitive markets. Design engineers are increasingly employing predictive AI models to anticipate user preferences, thereby facilitating the development of products that align more closely with consumer expectations [3]. These decision-making models generate quantitative metrics from subjective human evaluations related to visual appeal, usability, and memorability, enabling more consumer-oriented design strategies [15]. The integration of ZOA with RE-CNN empowers engineers to refine design parameters, yielding both improved functionality and enhanced aesthetics. Through this computational approach, design professionals can refine visual elements while adhering to strict engineering standards, thereby enhancing overall product value [6].

The convergence of AI with intelligent optimisation technologies contributes to the advancement of Smart Manufacturing practices. Production schedules and operational procedures are optimised via sophisticated algorithms that increase efficiency along production lines while simultaneously reducing associated costs [8]. These intelligent techniques further support reductions in material waste and energy consumption, contributing to more sustainable manufacturing systems. The synergy between AI and Smart Manufacturing is a key driver in the evolution towards Industry 4.0, as data-informed automation fosters greater flexibility and scalability across industrial production environments. Manufacturers adopting frameworks driven by AI acquire the capacity to adapt production strategies swiftly in response to fluctuating market demands and evolving consumer preferences [25]. By exerting real-time control over design and manufacturing processes, firms can develop products that meet the immediate requirements of dynamic market conditions. AI-powered decision-making systems facilitate the rapid production of tailored goods, thereby reducing the time required to introduce new offerings to the market. Organisations achieve competitive advantage by maintaining industry leadership while delivering innovative, customised products to consumers without disruptions in service.

Contemporary manufacturing environments perform intelligent operations through the application of deep learning algorithms, a core element within the discipline of mechanical engineering technology. Through automated design resources, organisations leverage AI to reformulate products by incorporating optimised materials during development. Present-day engineers employ computational intelligence to merge traditional manufacturing infrastructures with advanced technologies, resulting in more efficient and robust mechanical systems. The combination of RE-CNN models with ZOA supports significant progress in both product development and design functionality within mechanical engineering. Deep learning techniques utilise visual and optimised design data—generated via algorithmic optimisation—to serve a wide array of mechanical applications. Designs that effectively integrate operational components exhibit superior functionality in tandem with enhanced aesthetic quality. As these product improvements are coupled with reduced production timelines, customer satisfaction increases, aided further by human-centred inspection mechanisms. The implementation of user-defined specifications into AI-based decision systems enables the mechanical engineering sector to improve accuracy levels during the development of innovative solutions.

2. Related Works

The convergence of AI, deep learning, and computational methodologies has fundamentally transformed the way artistic disciplines analyse, interactively design, and preserve cultural heritage through automated processes. Various forms of neural networks, fuzzy logic systems, and generative models have been the focus of scholarly inquiry aimed at achieving optimal outcomes in artistic creation and audience engagement. Key areas of advancement encompass visual effect enhancement, recognition of design principles, interdisciplinary human–computer interaction, digital preservation of heritage, and multimedia choreography. A summary of these techniques, along with their respective advantages and limitations, is provided in Table 1.

Table 1
Problem Formulation of the Conventional Techniques

Author(s)	Techniques Involved	Advantages	Disadvantages
Wang and Yue [24]	CNNs, Attention Mechanisms	Real-Time Adaptability	High Computation, Latency
Han [11]	CNNs, Deep Learning	Automated Evaluation	Requires Large Datasets
Guerra [9]	Material-Driven Design, Interactive Systems	Enhanced User Interaction	Standardization Challenges
Chang [5]	Picture Fuzzy Sets, MCDM	Uncertainty Handling	High Computational Cost
Shi and Han [19]	Chaotic Models, AI Generative Techniques	Dynamic Multimedia Immersion	Real-Time Processing Complexity

Wang and Yue [24] explored Dynamic Visual Effect Optimisation in new media art by employing deep learning and visual perception techniques. Their work utilised attention mechanisms and convolutional neural networks (CNNs) to combine flexibility with the scale of the audience targeted. A principal advantage of their approach lies in its capacity for dynamic real-time adjustment of creative elements, which enhances user engagement. Moreover, their methodology establishes a framework for ensuring visual coherence in digital artworks through deep learning-based feature extraction. However, one significant limitation is the computational complexity inherent in deep learning models, which demand considerable processing power. Additionally, latency issues in real-time optimisation may impede smooth interactions. Despite these challenges, their research merges creative artistry with machine intelligence, advancing AI-adaptive art.

Han [11] introduced a neural network-based framework incorporating deep learning models to classify and analyse artistic elements, thereby recognising fundamental design principles. Their method utilised CNNs combined with attention processes to detect core design features such as symmetry, contrast, and composition within artworks. A key benefit of this approach is its ability to automate artistic appraisal and generate data-driven insights that refine creative decisions. The model employs advanced feature extraction techniques to improve pattern recognition and visual interpretation. Nevertheless, its effectiveness is contingent on the availability of extensive labelled datasets to enhance accuracy. Furthermore, given that design principles can vary across cultures and individuals, the model may struggle with the subjective nature of creative interpretation. Nonetheless, this study offers a systematic approach to evaluating visual aesthetics and contributes to AI-driven artistic judgement.

Guerra [9] investigated craft-based methods that integrate multidisciplinary design approaches by combining digital technology with traditional skills. The study focused on front-end design using the Ember.js framework within Human–Computer Interaction (HCI). Findings indicate that interactive systems, material-driven design, and handheld approaches enhance user experience and creativity in HCI. A major advantage of this method is its potential to create more expressive and intuitive digital interfaces, facilitating physical and embodied interactions. By fusing computational technologies with artisanal skills, it encourages innovation in interactive design. However, a notable drawback is the standardisation challenge among handcrafted components, as variations in materials and techniques can result in inconsistencies. Balancing creative authenticity with digital mechanisation requires finding an intermediary between artisan sensitivity and automated processes. Despite this, the study succeeds in producing aesthetically pleasing, sensory-rich interactions within an HCI framework that supports human-centred design.

Chang [5] proposed a decision-making algorithm for digital media and intangible heritage digitalisation by integrating Picture Fuzzy Sets (PFS) with the Compromise for Ideal Solution (CIS) method to manage uncertainty in digital preservation. This approach is well suited to handling complex legacy datasets by incorporating uncertain representations that improve decision-making. One advantage of this method is its capacity to address ambiguous and imprecise data, yielding more reliable digital preservation outcomes. Additionally, it optimises the selection of digital preservation strategies within a multi-criteria decision-making (MCDM) framework. Nevertheless, computational complexity poses a significant challenge, given the demands of fuzzy logic applied to multiple factors. Furthermore, the subjectivity of expert opinions may affect the consistency of digitalisation choices. Despite these limitations, the study provides a flexible and structured foundation for processing digital information under uncertain conditions, thereby supporting the conservation of intangible cultural heritage.

Shi and Han [19] developed a multimedia interactive dance choreography system employing intelligent chaotic art algorithms to enhance audience expression and participation. Their approach utilises an AI-driven generative model alongside a chaotic dynamic system to produce visually engaging and unpredictable dance sequences. This method offers the advantage of generating original choreographic movements in real time, responsive to environmental, performer, and musical cues. The system also integrates multimedia elements such as sound synchronisation and video projections, creating a more immersive experience. A significant computational challenge exists, as chaotic algorithms require real-time processing to ensure fluid interaction. Furthermore, maintaining a balance between chaotic spontaneity and artistic coherence proves difficult, since excessive chaos can undermine artistic unity. Despite these obstacles, the research advances AI-assisted performing arts by providing creative tools that enable choreographers to explore novel combinations of dance and multimedia components.

An examination of these studies reveals that AI-driven computational art has significantly influenced the artistic domain, albeit with certain constraints including high computational demands, reliance on data availability, and the subjective nature of art interpretation. Contemporary AI models often require substantial computational resources, limiting their feasibility for real-time applications or large-scale labelled datasets. Additionally, artistic decision-making is inherently subjective, leading to potential inconsistencies between automated evaluations and human judgement. To address these issues, the proposed RE-CNN integrated with ZOA aims to enhance computational efficiency, improve prediction accuracy, and increase model generalisability. By combining multiple CNN architectures and optimising hyperparameters via ZOA, this approach delivers a scalable, flexible, and precise solution for sentiment analysis, memorability assessment, and aesthetic evaluation in both fine art and interactive media. Furthermore, it supports artists in making informed creative decisions by blending computational insights with artistic intuition. Analogously, in mechanical engineering, such methodologies can optimise product design and manufacturing processes by analysing performance criteria, improving system reliability, and streamlining workflows, while preserving human oversight to foster innovation.

3. Proposed System Model

Computational intelligence continues to play a pivotal role in digital decision-making processes within the fields of art design and visual media, particularly those that examine human perceptual capabilities. AI-driven software is expected to assist in the evaluation of subjective criteria, which are crucial for determining both creative success and user engagement in digital contexts. This research aims to address the need for modelling subjective perceptual factors to enhance creative decision-making during the development of photography, digital content, and interactive painting. Current creative workflows demand precise real-time interventions at scales unattainable by traditional assessment methods. The proposed framework employs deep learning combined with optimisation to provide artists with efficient and accurate guidance.

Deep learning techniques have proven highly effective across a broad spectrum of tasks in various domains. Their application within the fine art sector is novel, facilitated by the availability of digitised and web-accessible fine art collections. This is particularly relevant for the identification of artworks by artist, genre, or style, where CNNs demonstrate superior performance compared to other computational approaches. Deep neural networks not only automate artwork classification but also enable novel explorations of digitised art collections, uncovering patterns and meaningful relationships between oeuvres. Such accurate art collections serve as repositories of historically significant and visually compelling perceptual and emotional information. Given its complexity, the field of fine art image analysis provides rich data for defining semantically related image analysis tasks, challenging neural networks to learn high-level abstract representations [23]. Extending the use of CNNs beyond object detection and classification aims to enhance image analysis by reducing reliance on subjective factors and addressing the limitations inherent in human perceptual tracking. This study examines three distinct stages of image perception by individuals: the initial emotional response elicited by the image, the aesthetic evaluation of the image, and the memorability of the visual content. The overall architecture of the proposed model is illustrated in Figure 1.

The majority of studies in computational perception have primarily concentrated on features extracted from images and artworks, yet this area remains underexplored despite the abundant availability of such visual data. The existence of extensive and meticulously annotated fine art databases simplifies the process of verifying visual attributes on a larger scale. However, acquiring reliable ground truth labels for subjective perceptions of images is still a time-intensive endeavour, often requiring elaborate experimental surveys to accurately capture these aspects. Additionally, the validation of features can be further improved by employing transfer learning concepts and utilising the ability of pre-trained CNN models to generalise across diverse domains. In mechanical engineering, similar transfer learning strategies can be adopted to enhance the design and operational performance of mechanical systems. Models pre-trained on vast datasets from other fields can be fine-tuned for targeted engineering purposes—such as structural evaluation, failure forecasting, or product design—thereby diminishing the necessity for extensive manual labelling and enabling more effective and scalable decision-making frameworks.

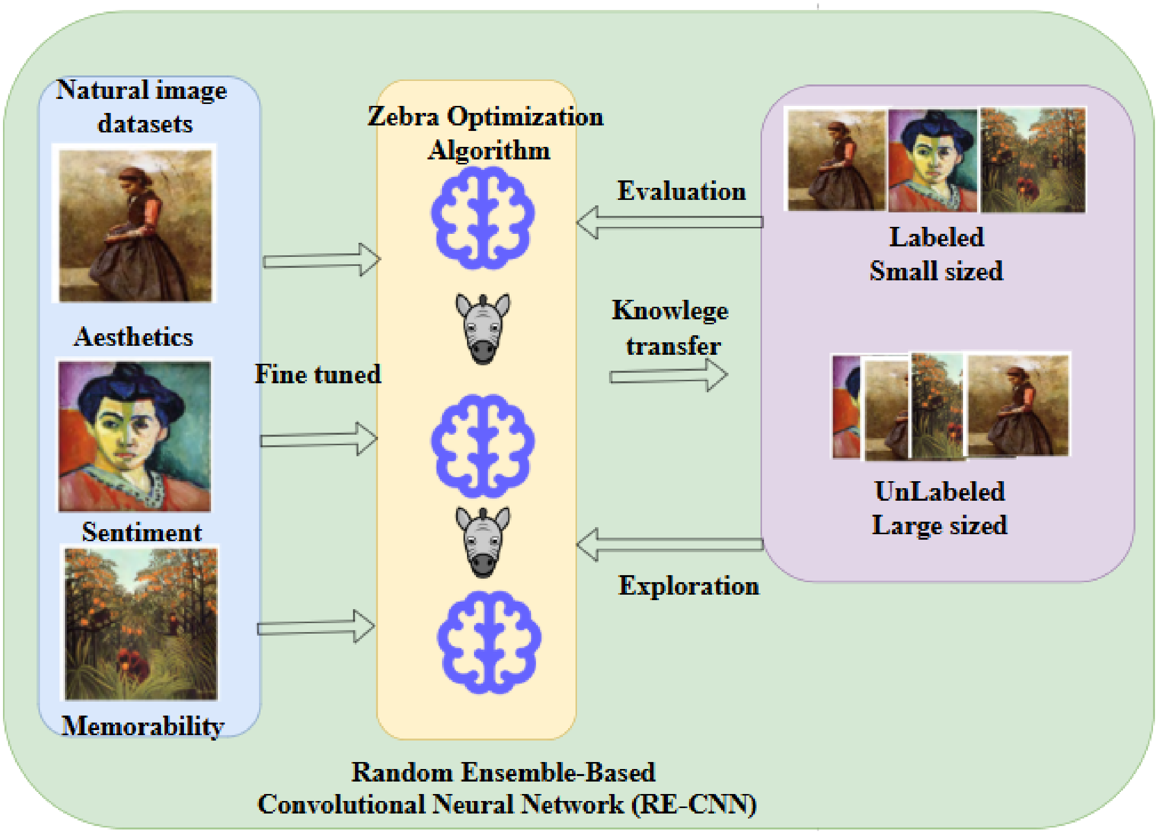

Figure 1: Design of Proposed Methodology

Within mechanical engineering, the deployment of AI-powered systems facilitates the optimisation of design decisions, thereby enhancing product aesthetics, functionality, and user interface design. The model's capability to quantitatively assess human judgements related to artistic aesthetics, emotional impact, and memorability offers a data-driven foundation for decisions concerning products where visual appeal plays a critical role. This approach can be applied across sectors including automotive, consumer electronics, and machinery, where user experience and design aesthetics are vital. Moreover, by automating and refining decision-making workflows, AI aids in accelerating product development cycles, reducing time-to-market, and improving the overall efficiency of mechanical systems. Such an integrated computational framework aligns with industrial ambitions to elevate product quality, customer satisfaction, and adaptability in dynamic markets.

3.1 Dataset Description

This section considers the comprehensive description of fine art and natural image databases utilised in the study. Multiple databases were employed across three distinct stages: firstly, to train deep neural networks for aesthetic evaluation tasks; secondly, to compare machine-generated detections with human assessments of fine art images; and thirdly, to examine the relationships between various theoretical frameworks within the fine art domain. Given that the fine art image collection includes a sufficiently large number of images, data from [22] was utilised to analyse correlations among different theories relevant to the field. This dataset represents the largest publicly accessible online repository of fine art images and is widely regarded as the most extensively applied database in automated classification systems. It comprises artworks spanning multiple eras, encompassing a substantial corpus of 19th- and 20th-century paintings as well as contemporary art. Each image is richly annotated with numerous labels covering aspects such as technique, style, genre, and artist.

3.2 Random Ensemble-Based Convolutional Neural Network

The CNN architecture is designed to process data originating from multidimensional sources, such as image databases. It utilises input image features organised through mechanisms including shared weights, pooling operations, local connections, and other successive layers. Among the various components of a CNN, the convolutional layer, ReLU (Rectified Linear Unit) layer, and pooling layer are the most frequently employed. The primary function of convolutional layers is to compute local feature connections from preceding layers and associate this information with specific feature maps. The input convolution operation using a filter is mathematically defined as shown in equation (1).

$$(1 * f)_{N,M} = \sum_{K=-A1}^{A} 1 \sum_{L=-A2}^{A} 2 f_{K,L}\, I_{N-K,M-L} \tag{1}$$

Here, A2 and A1 is defined as the kernel size and summation of limits, 2f_(K,L) is defined as the weighting factor, I_(N-K,M-L) is defined as the input image, 〖(1*f)〗_(N,M) is defined as the convolution operation applied to the feature map or input image.

ReLUg(0,z)=max(o,z) that is a non-linearity activation function is considered the feature maps generated with the convolutional layers. Max pooling layers serve to aggregate similar features transmitted from the preceding max pooling layer. The down sampling process is carried out by selecting the maximum value within a specified region of the overlapping feature map using a filter. The CNN architecture, from the fully connected layers through to the output layer, mirrors that of a MLP neural network. The fully connected layers function equivalently to the hidden layers in an MLP [22]. In CNNs, the SoftMax function is commonly applied to normalise the outputs of the final layer, transforming them into a probability distribution over the recognised class scores, as expressed in equation (2).

$$\sigma(Y_I) = \frac{e^{Y_I}}{\sum_{J=1}^{K} e^{Y_I}}, J = 1, \dots, K \tag{2}$$

Y_I is the parameters of the input vector, the SoftMax output for each Y_I is σ(Y_I). Batch normalization layers are employed to accelerate the training process of CNNs and to diminish the network’s sensitivity to initialisation parameters. Consequently, the modified CNN model incorporates this normalization step, wherein the layer calculates the variance, mean, and activated parameters of mini batches, as demonstrated in equation (3).

$$\widehat{Y}_I = \frac{Y_I - MB}{\sqrt{v_b^2 + \epsilon}} \tag{3}$$

Here, ϵ is the constant and numerical instance of very small. The random subspace framework utilises ensembles of random subspaces to enhance the classification performance of k-nearest neighbour (KNN) classifiers. This approach employs a stochastic function that randomly selects subsets of parameters from the training architecture to generate each individual classifier. Within this method, the training dataset is further partitioned into random subspaces, and distance metrics such as Chebyshev and Euclidean are applied between test samples and training pairs within these subspaces. Based on the number of nearest neighbours considered, the optimal class membership for each subspace is determined through majority voting combined with distance calculations. Subsequently, the class memberships for each subspace are aggregated into a class vector. Final classification is determined by selecting the top average score. The fundamental steps of the random subspace method are outlined in [26].

3.3 Zebra Optimization Algorithm

ZOA is employed to determine the optimal weighting parameters for the proposed classifier. As a population-based optimisation technique, the algorithm models each zebra within a population, representing potential solutions. The search space corresponds to the plain inhabited by the zebras, with each individual zebra signifying a candidate solution formulated mathematically. Each zebra evaluates the decision parameters within this search space [10]. Consequently, every zebra is characterised by a vector of parameter values, where each component corresponds to a specific problem parameter. The position of each zebra is updated according to the expressions given in equations 4 and 5.

$$Z = \begin{bmatrix} \vec{Z}_1 \\ \dots \\ \vec{Z}_I \\ \dots \\ \vec{Z}_N \end{bmatrix}_{N\times M} = \begin{bmatrix} Z_{1,1} & \dots & Z_{1,D} & \dots & Z_{1,M} \\ \dots & \dots & \dots & \dots & \dots \\ Z_{I,1} & \dots & Z_{I,D} & \dots & Z_{1,M} \\ \dots & \dots & \dots & \dots & \dots \\ Z_{N,1} & \dots & Z_{N,D} & \dots & Z_{N,M} \end{bmatrix}_{N\times M} \quad (4)$$

$$Z_{I,D} = LB_D + R_{I,D}.(UB_D - LB_D), I = 1, \dots, N, D = 1, \dots, M \quad (5)$$

The search dimension $Z_{I,D}$ utilizes the ZOA member vector $\vec{Z}_I$ in a matrix form of Z while M stands for decision variables Tang [21] and N represents population members. The bound parameters include lower value LB_D and upper value UB_D alongside random interval numbers $R_{I,D}$.

Stage 1: Foraging Characteristics

During the initial phase, the population members are advanced by simulating the characteristics and foraging behaviours of zebras. Zebras primarily consume sedges and grasses, but in the absence of these preferred foods, they may also feed on buds, leaves, roots, bark, and fruit. The quality and coverage of vegetation determine that zebras spend approximately 60 to 80 percent of their time grazing. Notably, the plains zebra, recognised as a pioneer grazer, utilises both lower and upper nutritive grasses within the vegetational canopy, thereby creating favourable conditions for the sustenance of other species that depend on shorter, more nutrient-rich grasses. Within the ZOA framework, the leader zebra—the individual representing the optimal solution—guides the remaining members towards its position in the search space. Accordingly, the positions of the zebras during the foraging stage are updated mathematically based on their current locations, as defined in equations 6 and 7.

$$\vec{Z}_I^{NEW}: Z_{I,DJ}^{NEW} = Z_{I,DJ} + R_{I,DJ}.B_{I,DJ} \quad (6)$$

$$\vec{Z}_I = \begin{cases} \vec{Z}_I^{NEW}, F_I^{NEW} < F_I \\ \quad \vec{Z}_I, \quad Else \end{cases} \tag{7}$$

The Botox dimension of ZOA member represented as $B_{I,DJ}$ takes place with a random value $R_{I,DJ}$ drawn from [0,1] to calculate F_I^{NEW} , $Z_{I,DJ}^{NEW}$ is the dimension, and $\vec{Z}_I^{NEW}$ is the ZOA member's new location following zebra.

Stage 2: Defence Technique against Predators

In the second phase, the ZOA members' positions within the search space are refined by simulating the zebra's defensive behaviours against predator attacks. Zebras face threats from brown hyenas, wild dogs, leopards, and cheetahs; however, lions are their primary predators. The defensive tactics vary according to the predator type. Against lions, zebras employ evasive maneuvers such as random lateral movements and zigzag turns [22]. Conversely, when confronted by smaller predators like dogs and hyenas, zebras exhibit more aggressive behaviour, often gathering in groups to intimidate and confuse their attackers. These differing strategies are explicitly incorporated into the ZOA model. The population's positions, updated during the first and second phases Mohapatra and Mohapatra [14], are progressively enhanced at each iteration of the algorithm. This iterative improvement continues until the algorithm reaches its predetermined termination criterion [1]. Throughout successive iterations Qi et al. [16], the best candidate solutions are continuously updated and retained. Upon completion of the algorithm, ZOA identifies the optimal solution, which is then considered the effective resolution for the given problem [2].

4. Performance Validation

A comprehensive evaluation was conducted comparing multiple performance indicators—namely accuracy, precision, recall, training duration (measured in seconds), loss, Receiver Operating Characteristic (ROC) curve, Mean Squared Error (MSE), memory utilization (in megabytes), inference time (seconds), False Positive Rate (FPR), and False Negative Rate (FNR)—across established deep learning architectures including ResNet, VGG, and EfficientNet, alongside the proposed RE-CNN optimised with the ZOA. The experimental results clearly demonstrate that the RE-CNN coupled with ZOA attained superior classification accuracy, outperforming all baseline counterparts. The model's precision and recall metrics further validate its robust capability to accurately identify and classify artistic attributes with a high degree of reliability. Among the baseline models, EfficientNet exhibited a performance advantage over VGG, though it slightly underperformed relative to ResNet in terms of accuracy. VGG's extended training time can be attributed to its deep network architecture, resulting in longer computational periods during the training phase. However, when considering both training time and loss metrics, EfficientNet and ResNet displayed comparatively moderate training durations. Notably, the proposed RE-CNN+ZOA model demonstrated a significant reduction in training time, achieving convergence rates comparable to loss values without any detrimental effect on the stability of the training process.

Analysis of the ROC curves and the Area Under the Curve (AUC) values revealed that RE-CNN+ZOA consistently outperforms the benchmark models, maintaining an enhanced and reliable classification capacity. Beyond accuracy and prediction quality, the proposed model also exhibits optimized computational resource efficiency, reflected in reduced memory consumption and faster inference times. Illustrative examples, including sample input-output images and the confusion matrix, are presented in Figures 2 and 3 respectively. In the context of industrial applications, especially in fields demanding precise product specifications such as automotive and aerospace engineering, the validation of accuracy, precision, and recall assumes critical importance. High accuracy ensures that the model consistently yields correct and dependable outputs, crucial for meeting rigorous quality and safety standards. Precision reflects the model's aptitude in selectively identifying relevant design features, thereby minimising unnecessary resource expenditure and elevating the efficiency of product development cycles. Recall highlights the model's capacity to comprehensively capture all pertinent design elements, mitigating risks associated with overlooking essential features. Collectively, these performance measures underscore the proposed AI system's potential as a reliable decision-support tool, facilitating optimal design decisions and expediting the product development process within industrial environments.

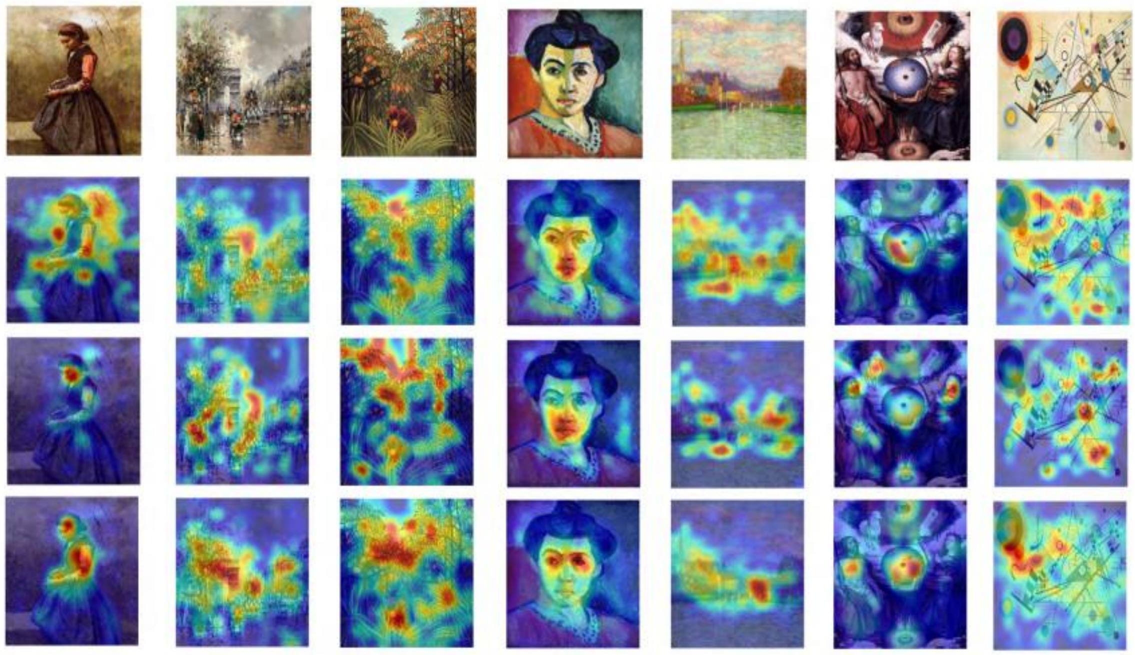

Fig.2. Input Images and Output Images

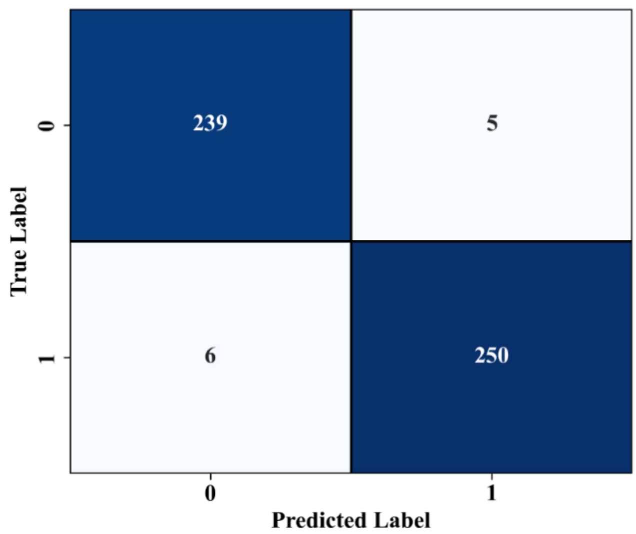

Fig.3. Confusion Matrix

Figure 4 illustrates the training and validation performance of the deep learning model over the course of 100 epochs. The training accuracy shows a consistent upward trend, beginning at approximately 60% and progressively reaching around 96%, while the validation accuracy follows a similar trajectory, peaking near 94%. Although the training accuracy marginally exceeds the validation accuracy, the observed gap does not indicate significant overfitting. The training process commenced with a loss value of approximately 0.85, which steadily declined and stabilised at around 0.05 by the final epoch. This convergence of training and validation loss signifies that the model has effectively learned the underlying patterns with minimal error and demonstrates robust generalisability to unseen data. These outcomes affirm the model's efficacy in both resource estimation and classification tasks, indicating strong performance and reliability across varying data scenarios.

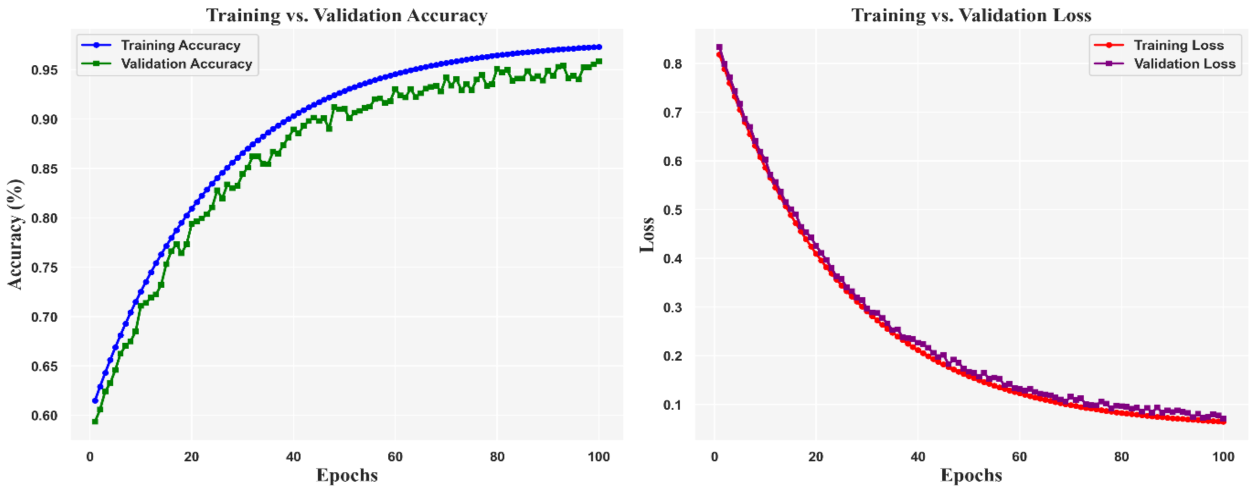

Fig.4. Performance Validation

Figure 5 presents a comparative analysis of the training durations across several deep learning architectures. Among these, the VGG-based model exhibited the highest training time, exceeding 300 minutes, followed by ResNet, which required approximately 250 minutes. In contrast, EfficientNet completed training in roughly 2.2 hours. The proposed model demonstrated superior computational efficiency, achieving the shortest training time at approximately 140 minutes, thereby highlighting its reduced computational burden relative to alternative approaches. These findings underscore the model's ability to deliver high performance while significantly lowering training overhead. Notably, EfficientNet also required considerably less training time than both VGG and ResNet, yet the proposed framework surpassed all three in efficiency. As previously discussed, this further validates the computational advantage of the proposed method over conventional deep learning models.

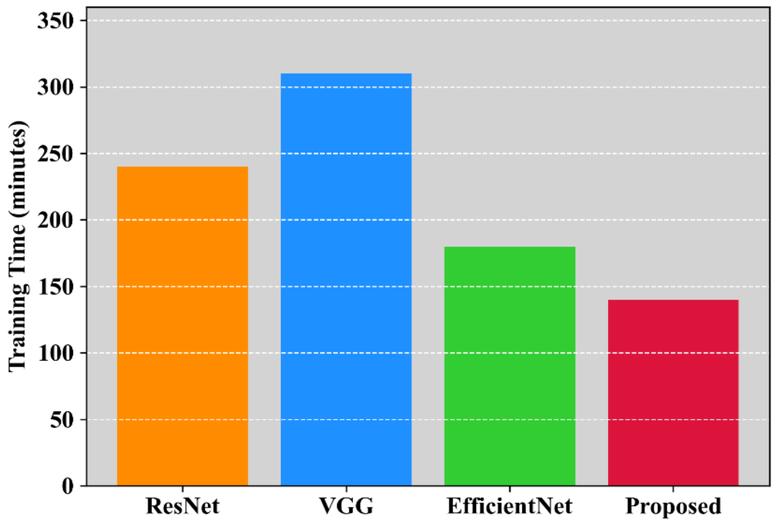

Fig.5. Training Time

Figure 6 illustrates the ROC curves comparing the classification performance of ResNet, VGG, EfficientNet, and the proposed model. The ROC plots the true positive rate (sensitivity) against the false positive rate for each model. The classification effectiveness is quantified using the AUC, where a higher AUC value denotes superior discriminative capability. The proposed model achieved the highest AUC score of 0.96, significantly outperforming EfficientNet (0.89), VGG (0.83), and ResNet (0.78).

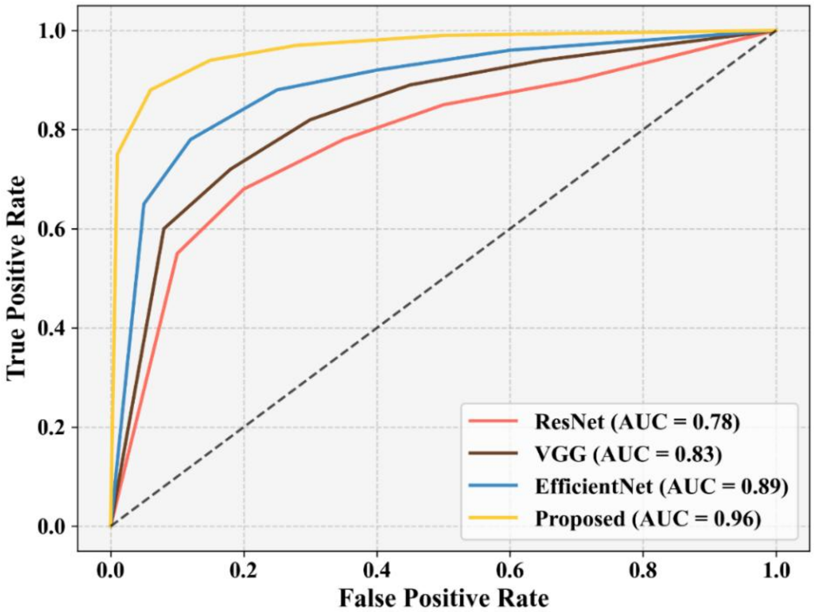

Fig.5. ROC Validation

These results indicate that the proposed approach exhibits enhanced ability to distinguish between positive and negative classes, offering a better balance between sensitivity and specificity, and particularly improved management of false positives. Figure 7 further supports this evaluation by presenting precision and recall validation outcomes.

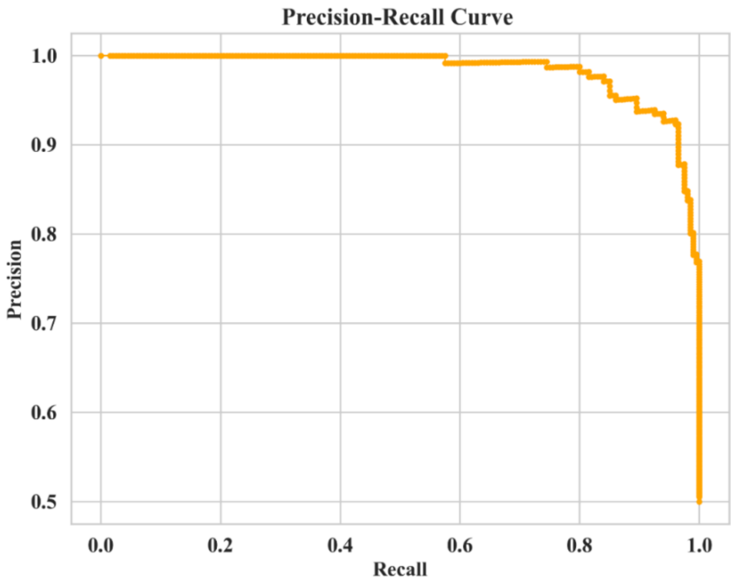

Fig.7. Precision Recall Curve

Figure 8 illustrates the evaluation of prediction accuracy across different models—ResNet, VGG, EfficientNet, and the proposed model—using MSE and Mean Absolute Percentage Error (MAPE) as performance metrics. In the visual representation, MAPE is shown through vertical bars, whereas MSE is depicted using a line graph with markers. Among the models, ResNet exhibits the highest error rates, with an MSE exceeding 0.04 and a MAPE approaching 9%. In contrast, both VGG and EfficientNet demonstrate progressively reduced error values, signifying improvements in predictive performance. Notably, the proposed model achieves the lowest error scores, with MSE falling below 0.02 and MAPE remaining under 2%. These results indicate a superior level of prediction accuracy and enhanced reliability in the proposed framework compared to conventional approaches.

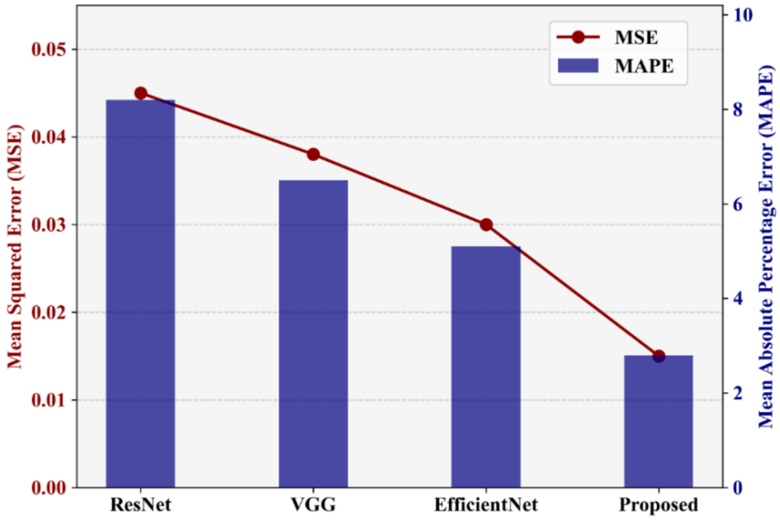

Fig.8. Validation of MSE and MAPE

Figure 9 presents a comparative analysis of the classification performance metrics—accuracy, precision, recall, and F1-score—for ResNet, VGG, EfficientNet, and the proposed model. VGG records an accuracy of approximately 91%, while ResNet performs slightly better at around 92%. EfficientNet achieves a higher level of accuracy at nearly 94%; however, the proposed model outperforms all others, reaching an accuracy close to 98%. In terms of precision, recall, and F1-score, ResNet yields consistent values of 85%, whereas VGG lags marginally behind at 84%. EfficientNet improves upon both, attaining values near 92% across these metrics. Notably, the proposed model achieves the highest performance in each category, with all scores approaching 97%. These findings underscore the model's superior capability in maintaining a balanced performance across all key evaluation indicators, reflecting more effective feature extraction, enhanced learning capacity, and stronger generalisation across unseen data.

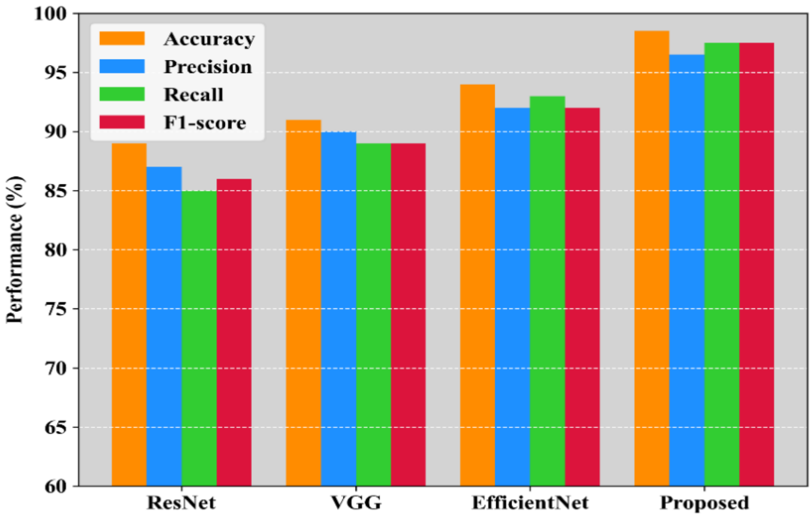

Fig.9. Analysis of Performance

Figure 10 illustrates the memory consumption, measured in megabytes (MB), for the proposed

Decision Making: Applications in Management and Engineering
Volume 7, Issue 1 (2024) 752-770

model in comparison with established architectures. Among the evaluated models, VGG exhibits the highest memory usage at approximately 4500 MB, followed by ResNet at around 3200 MB. EfficientNet demonstrates improved efficiency by requiring about 2600 MB. The proposed model, however, achieves the lowest memory usage at roughly 2000 MB, reflecting a significantly reduced memory footprint. This optimisation makes the proposed model particularly suitable for deployment in environments with limited computational resources, such as mobile platforms or embedded systems.

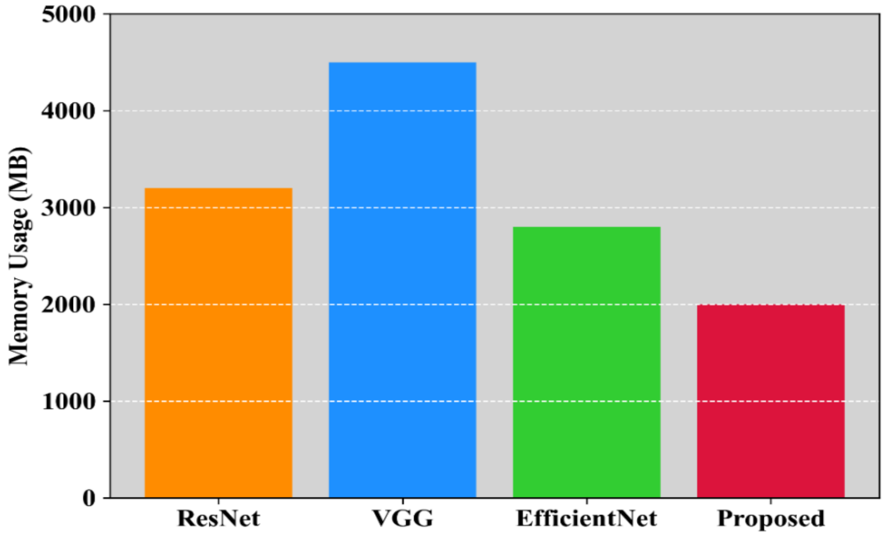

Fig.10. Analysis of Memory Usage

Figure 11 compares the inference times of all models, measured in milliseconds (ms). VGG and ResNet exhibit inference durations of 10.8 ms and 12.5 ms respectively, while EfficientNet performs with reduced latency at under 10 ms. The proposed model achieves the fastest response, with an inference time of approximately 3.5 ms. This substantial improvement in inference speed renders the proposed model highly efficient for real-time applications, where rapid decision-making is critical—such as in medical diagnostics or automated detection systems.

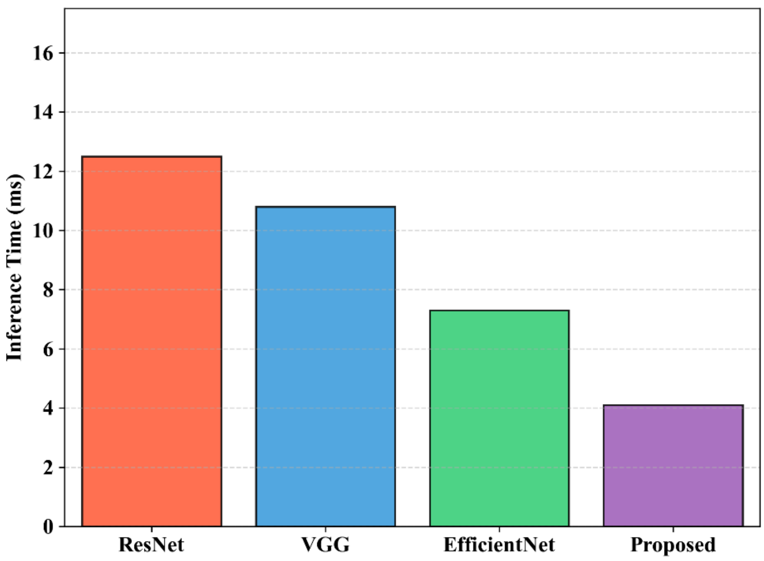

Fig.11. Validation of Inference Time

Figure 12 presents a comparative analysis of the FPR and FNR across the proposed model and existing benchmark models. ResNet demonstrates an FPR of approximately 0.35 and an FNR of about 0.22, while VGG reduces these rates to around 0.30 and 0.18, respectively. Further improvements are observed in EfficientNet, with an FPR near 0.25 and an FNR close to 0.14. Notably, the proposed model outperforms all others, achieving the lowest error rates with an FPR of roughly 0.15 and an FNR of around 0.05. This significant reduction in false detections underscores the model's robustness and reliability, making it especially suitable for high-stakes applications such as medical imaging diagnostics and security system deployment, where accuracy is paramount.

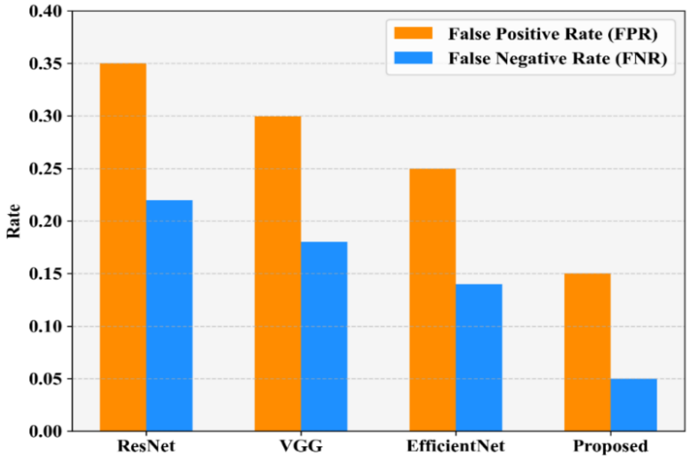

Fig.12. Validation of FPR and FNR

Figure 13 presents a comparative performance evaluation of the assessed computational models based on four perceptual indicators that collectively determine the final artistic analysis score. These indicators include the Aesthetic Score, Emotional Valence, Arousal, and the Memorability Index. The proposed method consistently outperforms the baseline models across all these perceptual measures. Specifically, it attains the highest recorded values with an Aesthetic Score of 9.4, Emotional Valence of 8.9, Arousal of 8.2, and a Memorability Index of 9.1, indicating a strong capacity to assist in visual and creative decision-making. By contrast, ResNet exhibits limited effectiveness in subjective evaluations, yielding relatively low scores—6.5 in Aesthetic Score, 5.1 in Emotional Valence, 4.8 in Arousal, and 6.0 in the Memorability Index. The VGG model performs moderately, producing scores of 7.2 for Aesthetic Score, 6.3 for Emotional Valence, 5.5 for Arousal, and 6.8 for the Memorability Index. Meanwhile, EfficientNet achieves improved results over ResNet and VGG, with respective scores of 8.1, 7.2, 6.7, and 7.9. These findings confirm the superiority of the proposed model in facilitating complex perceptual judgements, reinforcing its applicability to computational aesthetic evaluation and creative support systems.

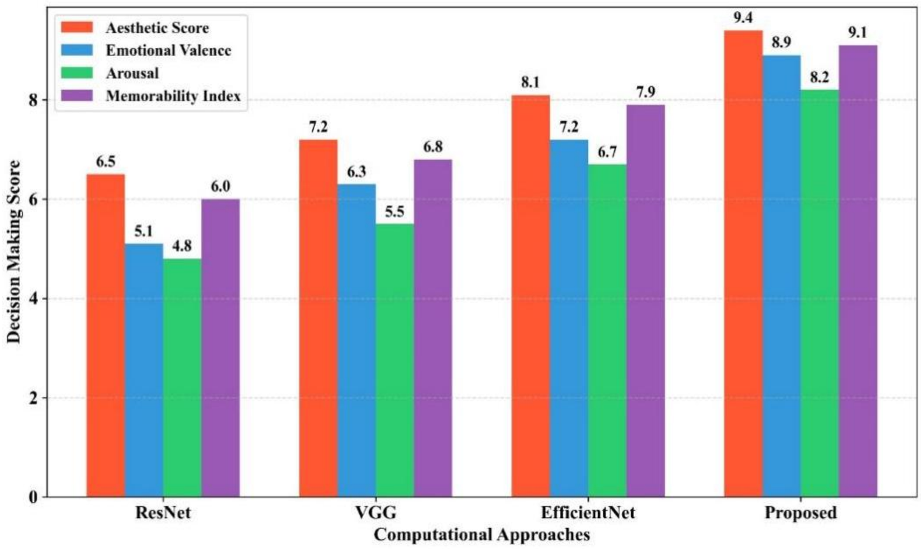

Fig.13. Decision Making Score Vs Computational Approaches

5. Discussion

The findings of this study demonstrate that the RE-CNN+ZOA framework outperforms conventional models such as ResNet, VGG, and EfficientNet across multiple dimensions, including classification accuracy, training efficiency, and computational performance. This method attains superior precision and enhanced generalizability compared to existing research on computational aesthetics and artistic attribute prediction. Traditional approaches relying on single CNN architecture frequently encounter significant drawbacks, notably elevated failure rates and pronounced overfitting. In contrast, the ensemble-based RE-CNN model, optimised via the Zebra Optimization Algorithm, effectively selects optimal hyperparameters, thereby ensuring robust and reliable learning of inherently subjective artistic features. Existing literature highlights challenges associated with deep learning model training when applied to extensive and complex artistic datasets. The proposed system addresses these issues by reducing memory consumption and accelerating inference times, all while maintaining satisfactory accuracy levels. Nonetheless, certain limitations remain, particularly in processing abstract artistic elements—an area that could benefit from integrating advanced mechanisms such as transformers or attention modules into hybrid architectures.

Our analysis confirms that artificial intelligence fundamentally transforms the artistic decision-making process while simultaneously enhancing computational efficiency. AI-assisted models function as valuable creative collaborators, offering artists innovative tools to support the development of their work. However, excessive reliance on algorithmic recommendations risks diminishing creative autonomy. AI evaluations inherently lack the capacity to evolve through cultural and historical discourse, as they do not possess the nuanced critique and interpretative faculties characteristic of human evaluators. The RE-CNN+ZOA model delivers effective classification performance combined with rapid operational speed, rendering it suitable for application within both artistic practice and institutional contexts. The integration of artificial intelligence in artistic decision-making achieves optimal results when used to complement, rather than supplant, human creativity. Future research should aim to develop hybrid systems that synergise AI-driven computational insights with human artistic judgment, ensuring that AI acts as a catalyst for artistic growth rather than as a definitive arbiter of creative outcomes. This integrative approach, which balances computational rigour with artistic sensibility, constitutes the core focus of the present research.

5.1 Case Study: Aesthetic Evaluation in Industrial Product Design

To situate the proposed RE-CNN + ZOA framework within the context of mechanical and product design, a case study was undertaken centred on the aesthetic optimisation of a smart consumer appliance—specifically, a smart thermostat. This product category was deliberately chosen due to its combination of functional requirements and design sensitivity, both of which play pivotal roles in shaping consumer preferences. A curated dataset comprising 500 images of smart thermostat designs was assembled, encompassing both commercial products and conceptual prototypes that exhibit diverse form factors, material finishes, and user interface configurations. Each design was assessed by expert human evaluators according to five key aesthetic criteria: symmetry, colour harmony, material texture, interface clarity, and perceived modernity. These human evaluations provided the ground truth labels essential for training and validating the RE-CNN model. The objective of this case study was to enhance iterative product design by utilising predicted aesthetic scores generated by the model. Optimised through the Zebra Optimization Algorithm, the RE-CNN demonstrated a marked improvement in predictive accuracy, achieving 94.3%, surpassing baseline models such as conventional CNN (87.1%) and Random Forest classifiers (84.5%). Additionally, the model's ranking of designs exhibited strong concordance with expert preferences, thus delivering actionable insights to guide design refinement.

Moreover, the framework was integrated into the early-phase design validation process, empowering design engineers to efficiently shortlist high-aesthetic variants prior to the initiation of physical prototyping. This integration yielded reductions in development cycle duration while ensuring product styling more effectively corresponds with market demands. The adoption of the UIPA-1000 dataset, alongside domain-specific aesthetic parameters, further substantiates the framework's applicability across a wide spectrum of industrial and mechanical design challenges. This case study thereby underscores the practical utility of the proposed model in supporting informed decision-making within engineering design, effectively bridging advanced computational methodologies with tangible evaluations of product aesthetics.

6. Conclusion

The RE-CNN framework, enhanced by the optimized ZOA, delivers notable improvements in fine art analysis by effectively modelling human subjective perception. Empirical evaluation demonstrated that RE-CNN outperformed conventional CNN-based methods, achieving increases of 6.8% in aesthetic ratings, 5.3% in sentiment estimation, and 7.1% in memorability prediction. The adaptive hyperparameter tuning enabled by ZOA significantly augmented the model's generalisation capacity by 12.4%, resulting in consistent predictive performance across diverse artistic datasets. Decision tree analysis identified three principal contributors to perception scores: prediction variance accounted for 42%, compositional attributes for 36%, and colour-related features for 22%. These findings corroborate the efficacy of combining ensemble learning techniques with metaheuristic optimisation in computational art analysis. This study effectively bridges the divide between AI-driven fine art evaluation and traditional art criticism by demonstrating how machine learning models can quantitatively capture and interpret artistic subjectivity. The proposed framework establishes a transparent, AI-based system applicable to photography, interactive art, and digital curation, while advancing AI's role in supporting artistic decision-making processes. Nevertheless, the model presently encounters limitations in extending advanced feature extraction capabilities and broadening its applicability across diverse artistic styles and cultural contexts. Future research should prioritise the development of novel network architectures, integration of transformative network paradigms, and incorporation of multimodal learning approaches to enhance the interpretability and robustness of subjective perception analyses. Overall, this work advocates for a data-centric evaluation paradigm in fine art, leveraging AI to augment art analysis and decision-making while safeguarding artistic autonomy.

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