e-ISSN: 2614-8404
p-ISSN: 2776-3234

Deep Learning-Based Consumer Preference Analysis for Batik Packaging Design Using Convolutional Neural Networks

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Abstract − *Packaging design plays an essential role in shaping consumers' first impressions of a product, particularly in the batik industry, where cultural meaning and visual identity are deeply intertwined. This study aims to explore how a Convolutional Neural Network (CNN) can help identify consumer preferences toward various batik packaging designs. The dataset consists of real packaging from local SMEs as well as prototype designs created specifically for this research, incorporating variations in motifs, colors, and structural formats. All images were standardized and normalized to ensure consistency before being processed by the CNN model. The architecture consists of several convolutional layers, pooling layers, and fully connected layers, with dropout applied to reduce overfitting. Model training was conducted using the Adam optimizer and the sparse categorical cross-entropy loss function. The results demonstrate that the model achieved a testing accuracy of 92.51%. Stable performance across precision, recall, and F1-score indicates that the CNN effectively captures visual patterns associated with consumer appeal. These findings highlight the potential for batik SMEs to utilize deep learning as a decision-support tool, enabling them to design packaging that is more appealing, relevant, and aligned with contemporary consumer preferences.*

Keywords – *Convolutional Neural Network, batik packaging, consumer preference, visual design, SME, deep learning*

e-ISSN: 2614-8404
p-ISSN: 2776-3234

I. INTRODUCTION

Packaging design plays a vital role in shaping how consumers perceive a product and in guiding their purchasing decisions. More than just a container, it becomes a visual language that expresses product identity, cultural values, and brand character. In today's world, especially when highlighting traditional motifs like batik, deep learning–based visual attention models can help elevate packaging aesthetics, making the product more appealing and meaningful to consumers [1]. Convolutional Neural Networks (CNNs) and Fully Convolutional Networks (FCNs) have been utilized to improve packaging design based on aesthetic aspects and cultural symbolism, with segmentation accuracy exceeding 96% [2][3]. Moreover, saliency mapping and logo detection using architectures like YOLOv8 combined with CNN-Transformer enable more effective visual analysis of packaging, helping to identify regions that draw consumer attention [4]. These models integrate object detection, saliency prediction, and brand-focused attention scoring to reveal how logo placement can influence consumer perception and brand recall [4].

Packaging design is more than just a container; it is a first touch, a silent conversation that takes place between a product and the consumer's heart. Especially in the world of batik, a rich cultural heritage, the packaging carries stories, traditions, and the dedication of the artisans. For Micro, Small, and Medium Enterprises (MSMEs), packaging is a reflection of their product's soul, an opportunity to touch the hearts of customers and stand out in a bustling market [5]. Research has long shown that packaging designed with empathy can trigger purchase intentions, build emotional bridges, and embed a lasting impression in the consumer's mind [6][7][8]. Thus, for every MSME, understanding what consumers truly want and feel about a design is not just a business challenge—it is a journey to find a genuine connection [9][10].

The analysis of cultural motifs on packaging, including papercutting and batik, using CNNs, shows that traditional features can support product differentiation and enhance consumers' emotional resonance [11]. Aesthetic-based recommendation models that integrate deep learning techniques such as CNN and GAN with consumer preference profiling have enabled large-scale, automated evaluation of packaging designs tailored to affective responses [12].

Conventional approaches to packaging design often rely on intuition or small-scale market research, which offers limited, deep, and measurable insights. With the advancement of technology, there is a growing need for more systematic and data-driven methods to analyze consumer preferences [13]. In recent years, the application of deep learning has revolutionized various fields, including consumer behavior analysis and digital marketing [3, 5, 6]. Models like Convolutional Neural Networks (CNNs) have proven highly effective in identifying complex visual patterns, making them an ideal tool for analyzing image-based design preferences [14][15][8].

Deep learning techniques, such as Fully Convolutional Networks (FCNs) and hybrid CNN-Transformer models, have proven effective for processing visual elements on packaging with high segmentation accuracy. An improved FCN model has demonstrated the ability to identify key components in packaging design, such as logos, text, and decorative motifs, with classification accuracy reaching 96.84% on specialized packaging datasets [16]. This demonstrates that deep learning is not only capable of visual recognition but also of understanding the structural aesthetics that influence consumer perception and product appeal. Furthermore, aesthetic-based recommendation systems that combine CNN and GAN technologies guided by consumer aesthetic preferences offer automated solutions for generating packaging designs that are both attractive and preferred by end-users. For instance, a study using Continuous Conditional GAN (CcGAN) successfully incorporated large-scale user preferences to create packaging designs in a semi-supervised manner [7]. This framework offers promising opportunities for batik SMEs to streamline packaging design processes that align with market expectations.

Nevertheless, research that specifically applies CNNs to analyze consumer preferences for batik packaging design, with a focus on the challenges faced by MSMEs, remains very limited. Most existing studies focus on sentiment analysis from online reviews or general purchase behavior prediction [4, 7], without delving deeply into the visual elements of packaging design. There is a significant research gap in applying artificial intelligence to identify cultural and semiotic patterns in packaging design that can influence consumer appeal, particularly in the context of cultural heritage like batik [8, 9]. Furthermore, the integration of this technology as a practical framework to support MSMEs in design decision-making is rarely discussed [17][18][19].

Deep learning techniques like Fully Convolutional Network (FCN) have demonstrated high effectiveness in processing visual elements on packaging. Based on experiments using a packaging design dataset, an FCN model enhanced with a superpixel-assisted ISS method achieved a segmentation accuracy of 96.84%, with an average segmentation error of only 1.42% and a false-alarm rate of approximately 2.78% [16][8]. These results provide a strong foundation for applying FCN models to detect and analyze the most visually engaging elements in batik packaging designs.

Therefore, this study aims to address this gap by developing a CNN-based approach to analyze consumer visual preferences for batik packaging design. We seek to build a model that can identify the most influential design attributes, such as motifs, colors, and layouts, and provide insights that can be directly applied by MSME actors. The

e-ISSN: 2614-8404
p-ISSN: 2776-3234

main contributions of this research are: 1) The application of CNNs to analyze visual preferences for batik packaging, providing a new, more measurable methodology; 2) The development of a predictive model that can help MSMEs make data-driven design decisions; and 3) The provision of a framework for utilizing AI technology to enhance the competitiveness of MSMEs in the digital market [20][21]. The findings of this research will not only enrich the literature in the field of Informatics and Computer Science but also offer practical solutions relevant to the local economic context in Indonesia.

Packaging design plays a crucial role in capturing consumer attention, particularly in industries rooted in cultural heritage such as batik. The visual complexity and symbolic richness of batik motifs require sophisticated computational approaches to understand how consumers interact with packaging elements. Recent advances in computer vision have enabled the use of Convolutional Neural Networks (CNNs) to identify and segment visually salient regions in packaging layouts [8][16]. For instance, improved Fully Convolutional Networks (FCNs) have been applied to decompose packaging components, facilitating the identification of visual elements that most significantly drive consumer engagement [16].

Recent advances in deep learning have shown that combining convolutional neural networks (CNNs) with transformer-based saliency models can effectively identify visual hotspots in packaging design. Saliency map prediction, especially when compared to human eye-tracking data, can highlight which regions of a package—such as logos or traditional motifs—are most visually engaging to consumers. This technique has proven particularly useful in packaging research, where brand visibility and focal point positioning influence consumer decision-making [22][3][8]. These multimodal approaches hold substantial potential for exploring consumer preferences in batik-inspired packaging, enabling SMEs to enhance visual appeal and cultural resonance in international markets.

Research published in the *Asia Pacific Journal of Marketing and Logistics* examined the semiotic impact of packaging design on brand image, perceived quality, brand loyalty, and consumer purchase intention. The study concluded that integrating semiotic elements such as colors, symbols, and typography into packaging can significantly improve brand image and perceived product quality, ultimately fostering stronger brand loyalty and purchase intention. These findings are framed within the stimulus organism response (SOR) theoretical model [10].

Studies on the use of metaphors derived from traditional cultural symbols reveal that packaging designs featuring ritualistic or local motifs directly and indirectly influence consumers' perceived emotional value and purchase intention. These symbolic elements evoke emotional resonance, particularly when aligned with cultural familiarity. Moreover, consumer cultural identity plays a mediating role between consumption experience and perceived value, thereby reinforcing brand engagement and loyalty [23]. Complementing this, research based on the stimulus organism response (SOR) framework has shown that semiotic elements in packaging positively impact brand image and perceived quality, which in turn strengthen brand loyalty and purchase intention [24].

Sustainable packaging has become a vital factor in modern consumer preferences, especially within cultural and craft product sectors such as batik. Studies have shown that sustainability attributes such as the use of recycled materials, compostability, and eco-friendly design significantly enhance consumers' perceived value and purchase intention. Furthermore, the integration of batik motifs into eco-conscious packaging allows SMEs to combine culturally authentic aesthetics with consumer demand for environmental responsibility, strengthening both market appeal and brand value [25][26][27][28].

Sustainable and eco-friendly packaging has emerged as a central element influencing modern consumer preferences. Features such as bioplastics and plastic-free materials have been shown to significantly enhance purchase intentions. Environmental consciousness, consumers' willingness to pay a premium, and the level of trust in sustainable practices are also key drivers that increase interest in products utilizing eco-conscious packaging. When combined with cultural visual elements such as traditional batik motifs, packaging not only delivers environmental value but also strengthens the product's emotional and aesthetic appeal, aligning with the values of socially and environmentally aware consumers [29][30].

Studies in the food segment, such as juice pouches, show that packaging materials and label claims significantly influence consumer decisions, enabling premium and sustainable presentation— even when incorporating distinctive batik motifs [31]. Despite many technical advancements, the current use of CNNs for batik-specific motif detection in packaging remains minimal, highlighting a research gap that is particularly strategic for batik SMEs [32]. Therefore, the present study aims to develop a Grad-CAM-based CNN framework to classify consumer preferences for batik packaging designs, identify key visual features, and offer actionable visual recommendations to help SMEs enhance competitive positioning [4][33]

II. RESEARCH METHODOLOGY

This study employs a quantitative experimental design grounded in deep learning, particularly Convolutional Neural

e-ISSN: 2614-8404
p-ISSN: 2776-3234

Networks (CNN), to explore consumer responses to batik packaging's visual design. CNN was selected for its demonstrated strength in recognizing intricate visual patterns. One application of CNN in packaging aesthetics involved the evaluation of consumer perception by distinguishing visually appealing traditional motifs from less attractive ones, with higher accuracy than conventional methods [34]. In a related study, deep learning techniques were utilized to extract color and texture features in agricultural packaging, reinforcing CNN's effectiveness in capturing key visual cues that support design innovation [35]. These studies confirm the synergy between AI-driven feature extraction and human visual perception, offering a robust, data-driven foundation for designing batik packaging that resonates aesthetically with consumers

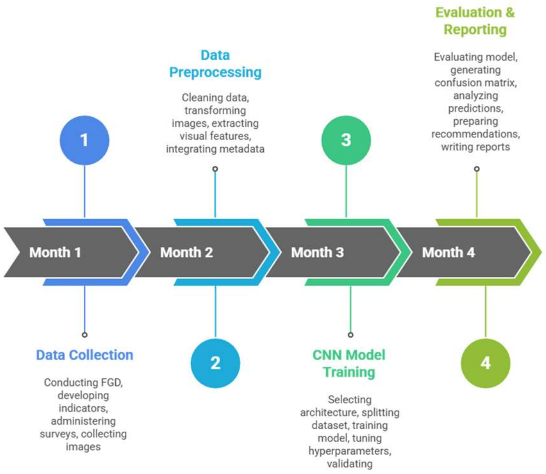


Figure 1. Research Flow Diagram

2.1 Data Collection

This study collects two primary types of data. The first consists of various visual designs of batik packaging, including existing packaging used by SMEs, as well as prototype designs specifically developed by the researchers. These prototypes explore variations in elements such as batik motifs, color schemes, packaging structure, and layout. This dual approach enables a comprehensive analysis of the visual characteristics that influence consumer perception essential aspect in product design research [36].

In parallel, consumer preference data are collected through an online survey distributed to a representative sample of consumers, aligned with methodologies of recent studies that examined how packaging elements such as color and shape impact consumer decisions using online questionnaires [37].

Lastly, particular attention is given to the quality of collected images. All visual data are ensured to meet minimum standards for resolution and format compatibility, which is essential to optimize their effectiveness in CNN model processing. High-quality image input is a key requirement for reliable performance in deep learning applications involving visual analysis [38].

2.1.1 Dataset of Batik Packaging Designs

The batik packaging design images were collected from two primary sources: (1) an archive of existing packaging used by batik SMEs in the Cirebon region, and (2) a series of prototype designs deliberately created for this study. These prototypes incorporated controlled variations in key visual elements such as traditional and contemporary batik motifs, diverse color schemes, eco-friendly packaging materials, and multiple structural formats including boxes, pouches, tubes, and foldable models. This combination enabled the formation of a representative and diversified dataset that reflects real-world design variability [39][40].

All images were digitized in standard formats (JPG and PNG) and curated to meet a minimum resolution threshold of 1024×768 pixels. Ensuring visual clarity is essential to maintain the performance and reliability of the CNN during training and inference. Previous research has shown that deep learning models exhibit significant drops in classification accuracy when trained on low-resolution or artifact-prone images [40].

The final dataset, therefore, comprises a high-quality, visually rich, and uniquely diverse collection of batik packaging designs, making it suitable as the primary input for visual pattern recognition tasks in this deep learning-based analysis [41].

2.1.2 Consumer Preference Data

Consumer preference data reflects how consumers evaluate batik packaging design attributes such as color, shape, motif, and composition via a binary classification (preferred vs. not preferred). This label serves as the target for training the CNN model to recognize visual patterns associated with consumer likes and dislikes. Valid and representative preference data are essential for building a reliable visual classification system that can inform design decisions. Evidence from neuromarketing and consumer behavior research shows that packaging visual elements significantly influence emotional responses and purchase behaviors, supporting the integration of consumer preference data into AI-driven packaging design [42][43].

2.2 Data Preprocessing

In image-based model training, the preprocessing stage plays a crucial role in ensuring consistent format and scale across input data. In this study, all images in the training, validation, and test datasets were resized to 150×150 pixels and normalized by dividing each pixel value by 255, scaling intensities to the [0,1] range. This combination of resizing

e-ISSN: 2614-8404
p-ISSN: 2776-3234

and normalization helps accelerate model convergence and prevents numerical instability during training procedures widely accepted in CNN-based computer vision workflows [44].
Additionally, the flow_from_directory() function (with class_mode='categorical') was used to automatically load images from structured directories, group them by class, and generate data batches of size 32 for both training and validation. This preprocessing approach has been empirically validated across diverse image classification domains as a method that promotes stable and efficient CNN model training [44].

2.3 Data Augmentation

To enhance the generalization capability of the model and reduce the risk of overfitting, data augmentation was applied to the training images using the ImageDataGenerator class. The augmentation parameters included rotation_range=20, zoom_range=0.2, and horizontal_flip=True. These transformations artificially increase the diversity of training images without adding new samples, thereby exposing the model to varied visual contexts during training.

This strategy improves the model's robustness to common real-world variations in shape, orientation, and scale, particularly relevant in complex visual domains like batik packaging design. In contrast, validation and test datasets were excluded from augmentation to ensure objective evaluation of model performance. Such augmentation techniques have been widely validated to enhance deep learning performance, especially in image classification tasks involving limited datasets [45][46].

2.4 CNN Model Developtment

This study developed a Convolutional Neural Network (CNN) model to classify batik packaging designs into two categories: "preferred" and "not preferred." The model was constructed using a sequential architecture, starting with three convolutional layers with 32, 64, and 128 filters, each with a 3×3 kernel. Each layer was followed by a MaxPooling2D layer to downsample the spatial dimensions while preserving essential features [47].

The resulting feature maps were flattened into a one-dimensional array and passed to a Dense layer with 128 neurons, followed by a Dropout layer (rate = 0.5) to mitigate overfitting. The final layer employed softmax activation to produce probabilistic output across the two classes.
The model was compiled using the sparse_categorical_crossentropy loss function, optimized with the Adam algorithm, and evaluated using accuracy. This configuration was effective in balancing computational efficiency with model complexity, suitable for extracting intricate patterns typical of batik designs. Prior studies have demonstrated that advanced FCN architectures can accurately segment packaging elements such as logos and motifs with accuracy reaching 96.84% [48], while CNNs integrated with transformer-based saliency prediction are proven effective in highlighting visual regions that influence consumer attention [49].

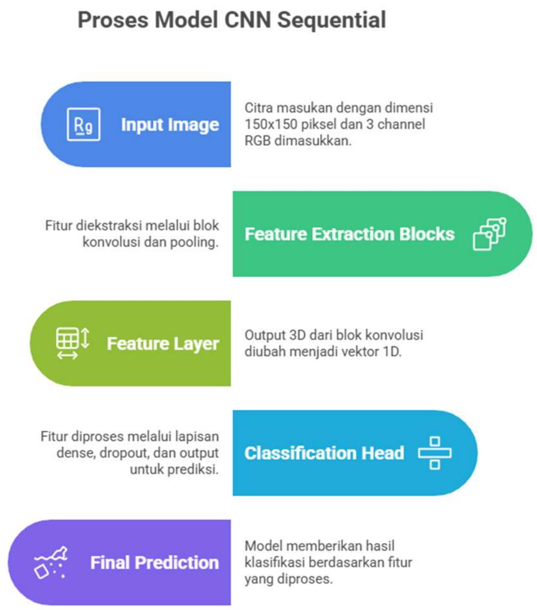


Figure 2. Model seguential

2.5 Model Training

The training of the Convolutional Neural Network (CNN) was specifically designed to analyze consumer preferences related to batik packaging design with optimal performance in mind [50]. All input images were standardized to a resolution of 150×150 pixels to ensure consistency across the dataset and compatibility with the CNN architecture [51]. The training process was conducted using a batch size of 32 over 15 epochs, a configuration chosen to balance computational efficiency and model accuracy across the training and validation phases [52].

To enhance model robustness and generalization, data augmentation was applied to the training set using the Image Data Generator class [53]. This augmentation strategy included rescaling pixel values to the [0,1] range, random rotations up to 20 degrees, zooming by up to 20%, and horizontal flipping. These techniques artificially increased the diversity of training data without requiring additional image samples, allowing the model to learn more invariant features. The model was compiled using the 'adam' optimizer and the sparse_categorical_crossentropy loss function, with accuracy selected as the main evaluation metric monitored throughout training [54].

The CNN model architecture adopted in this study consists of three consecutive Conv2D layers with 32, 64, and 128 filters, respectively, each followed by MaxPooling2D layers to progressively reduce the spatial dimensions of extracted features [55]. This hierarchical structure allows the network to learn both low-level and high-level visual features relevant to packaging design. The convolutional output is then passed through a Flatten layer, converting the multi-dimensional feature maps into a one-dimensional vector suitable for fully connected layers [56].

A Dense layer with 128 units and ReLU activation is added to learn abstract representations that correlate with consumer preferences. To enhance generalization and reduce overfitting, a Dropout layer with a rate of 0.5 is incorporated [57]. The final layer is a Dense output layer with softmax activation, where the number of units corresponds to the number of preference classes (train_generator.num_classes), enabling the model to assign probabilistic predictions for each class label [58]. In total, the architecture consists of approximately 4.83 million trainable parameters, providing a strong foundation for visual pattern recognition in the context of batik packaging design.

2.1 Model Evaluation

To assess model performance, standard classification metrics were used: accuracy, precision, recall, specificity, F1-score, and AUC-ROC [59][60]. Confusion matrices and ROC curves were plotted. To improve interpretability, SHAP (Shapley Additive Explanations) and LIME were employed to help uncover which features had the most significant influence on the model's predictions [61][62].

2.2 Community Participation and Validation

The Convolutional Neural Network (CNN) in this study was trained to predict consumer preferences regarding batik packaging design with an emphasis on optimal learning and generalization. All input images were standardized to 150×150 pixels to ensure uniformity and compatibility with the CNN architecture [47]. The training was conducted using a batch size of 32 for 15 epochs, balancing training efficiency with convergence stability [48].

To improve model generalization and minimize overfitting, data augmentation was applied using the Image Data Generator class. Augmentation techniques included pixel rescaling (1./255), random rotation (up to 20 degrees), zooming (±20%), and horizontal flipping. These transformations diversified the training set without increasing the dataset size, thus enhancing robustness against visual variability in packaging [45][63].

The CNN architecture comprised three Conv2D layers with increasing filters (32, 64, 128), each followed by MaxPooling2D layers to reduce spatial dimensionality and focus on essential visual patterns. The output was passed through a Flatten layer, followed by a Dense layer of 128 neurons with ReLU activation and a Dropout layer (rate = 0.5) to reduce overfitting[64][65]. The final Dense output layer with softmax activation produced probabilistic predictions for the two consumer preference classes.

The model was compiled using the Adam optimizer and the sparse categorical cross-entropy loss function, suitable for multi-class classification problems with integer-labeled targets [66]. Overall, the network included ~4.83 million trainable parameters, optimized for classifying complex visual patterns in batik packaging designs [67].

III. RESULTS AND DISCUSSION

This section presents the findings of the conducted research, structured sequentially from the model training results to the model testing results.

3.1 Data Collection

This research employed a dual data collection approach to ensure comprehensive coverage. The primary dataset consisted of images of existing batik packaging from various Micro, Small, and Medium-sized Enterprises (SMEs). In addition, custom-designed prototypes created by professional designers, with variations in motifs, color palettes, and packaging formats, were also included. The purpose of these prototypes was to broaden the dataset's variety, allowing the model to learn subtle features that might not be present in existing designs. Each image in the dataset was annotated based on consumer preferences (e.g., "Preferred" or "Not Preferred") through a survey, which served as the classification target for the model

Preferred_42 Preferred_46 Preferred_63 not_preferred_18 not_preferred_59 not_preferred_07

Figure 3. Data Colection

3.2 Data Preprocessing

To prepare the image data for training the Convolutional Neural Network (CNN) model, several preprocessing steps were undertaken. All images in the dataset, both from SMEs and prototypes, were uniformly resized to **150x150 pixels**. This step was crucial to ensure all inputs had the same dimensions, a standard requirement for neural network architectures. Furthermore, the pixel values of each image were normalized, i.e., their values were scaled from the original range of [0, 255] to a range of [0, 1]. This normalization helps to accelerate the training process and improve model stability by ensuring all

e-ISSN: 2614-8404
p-ISSN: 2776-3234

features are on a uniform scale.

3.3 Augmentation

To address data limitations and mitigate overfitting, data augmentation techniques were applied. This augmentation artificially expanded the training dataset by creating modified versions of existing images. The techniques used included:

- **Rotation:** Images were rotated at random angles.
- **Zoom:** Images were randomly zoomed in or out.
- **Horizontal Flip:** Images were flipped horizontally.

These steps significantly increased the variety within the training dataset, enabling the model to learn from a wider range of perspectives and conditions, thus improving its ability to generalize to new data.

3.4 CNN Model Developtment

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72, 72, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_2 (Conv2D)	(None, 34, 34, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 17, 17, 128)	0
flatten_1 (Flatten)	(None, 36992)	0
dense_2 (Dense)	(None, 128)	4,735,104
dropout (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 2)	258

Total params: 4,828,610 (18.42 MB)
Trainable params: 4,828,610 (18.42 MB)
Non-trainable params: 0 (0.00 B)

Figure 4. CNN Model Developtment

In this stage, a Convolutional Neural Network (CNN) model was developed using a sequential architecture. The model was designed to extract features from batik packaging images collected from SMEs and to classify them based on consumer preferences.

3.5. Model Training and Validation Results

The performance of the Convolutional Neural Network (CNN) model showed a consistent and promising increase throughout the 15 training epochs. The training accuracy steadily rose from 0.5239 in the first epoch to 0.9580 in the final epoch, indicating that the model successfully learned the patterns from the training data. Correspondingly, the training loss consistently decreased, ending at 0.0776, demonstrating that the model successfully minimized its prediction errors over time.

The validation accuracy also showed a positive trend, reflecting the model's ability to generalize to unseen data. The model reached its highest validation accuracy of 0.8772 at epochs 9 and 13, before stabilizing at 0.8553 in the final epoch. This consistency, coupled with a decrease in validation loss to 0.2441, highlights the robustness and reliability of the model in handling data outside the training set.

3.6. Model Testing Results

A comprehensive evaluation on the testing dataset further confirmed the model's strong predictive capability. The model achieved an overall testing accuracy of 0.9251 and a loss of 0.1989. Detailed classification metrics further highlight the model's ability to differentiate between preference categories: For the "Not Preferred" class, the model achieved a precision of 0.90, recall of 0.96, and an F1-score of 0.93. For the "Preferred" class, the model achieved a precision of 0.95, recall of 0.88, and an F1-score of 0.91.

3.2 Training and validation Acuracy

Figure 5. Training and Validation Acuracy.

The training and validation accuracy chart reveals a notable improvement in model performance during the early stages of training. Training accuracy surged rapidly from approximately 50% to over 90% by the second epoch, and continued to improve steadily, reaching nearly 95% by the 14th epoch. This consistent upward trajectory indicates that the model successfully learned complex visual patterns from the training dataset.

In parallel, the validation accuracy also experienced a sharp increase early on, reaching around 85% by epoch 2. While it fluctuated slightly between 82% and 88% throughout the remaining epochs, it remained within a stable and acceptable range. The gap between training and validation accuracy suggests a mild overfitting, yet the extent is not significant enough to undermine the model’s ability to generalize.

Overall, these trends suggest that the CNN model was not only effective in learning from the training data but also retained a reasonably strong generalization capability, making it suitable for real-world deployment in predicting consumer preferences toward batik packaging designs.

e-ISSN: 2614-8404
p-ISSN: 2776-3234

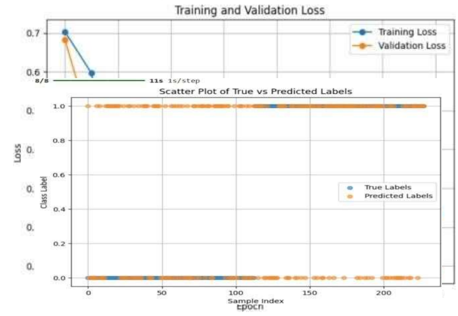


Figure 6. Traning and validation loss

Figure 7. Scater Plot of True vs Predicted label

The scatter plot provides a visual comparison between the actual labels (true labels) and the predictions made by the CNN model (predicted labels) for each sample in the test dataset. The X-axis represents the index of each test sample, while the Y-axis indicates the class label, with 0 denoting *not preferred* and 1 denoting *preferred*.

Blue dots in the plot correspond to the actual class labels, whereas orange dots represent the model's predictions. A strong overlap between the blue and orange points across both classes is observed, suggesting that the model's predictions closely match the true labels. Only a few orange points are misaligned with the blue ones, indicating that the number of incorrect predictions is relatively low. Overall, this scatter plot reinforces earlier findings that the CNN model achieved a high level of prediction accuracy. It demonstrates consistent performance in classifying consumer preferences for batik packaging designs based on visual features, with minimal misclassifications.

Beyond the accuracy metrics, it is essential to reflect on the explainability and fairness of the CNN model's predictions. Recent studies, such as by Jöchl and Uhl [1], have shown that deep learning models can exhibit content bias depending on how visual data is structured and learned. This insight is particularly important when models are deployed in culturally sensitive domains like batik packaging design, where interpretability is crucial to avoid misrepresentation or bias. By integrating explainability tools such as Grad-CAM, SHAP, or LIME, the decision-making process of the CNN can be made more transparent and trustworthy to stakeholders

This study set out to explore how a Convolutional Neural Network (CNN) could be used to understand what consumers prefer when it comes to batik packaging design, an area where culture, aesthetics, and technology meet. The results are both promising and encouraging. The CNN model successfully classified consumer preferences with a test accuracy of 92.51%, demonstrating its ability to learn and distinguish between designs that are visually appealing to consumers and those that are not. Throughout the training process, the model showed consistent progress, with accuracy rising from 0.5239 to 0.9580, and a steady drop in training loss. This upward trend tells us that the model was not only learning but learning effectively. While there were minor fluctuations in validation accuracy, the model still achieved a peak validation accuracy of 87.72%, showing it could handle unseen data reasonably well.

One of the key reasons behind this performance was the use of data augmentation. By simulating variations like image rotation, zoom, and horizontal flips the model learned to recognize design elements in various forms and perspectives, making it more resilient and adaptable. This is especially useful in a design context where real-world products often appear in different sizes, orientations, or packaging formats.

The classification report provides more depth to this success. For the class of "not preferred" designs, the model achieved a precision of 0.90 and a recall of 0.96, meaning it was very good at identifying which designs consumers tended to dislike. On the other hand, for "preferred" designs, it scored a precision of 0.95 and a recall of 0.88, which means the model was also strong in recognizing favorable designs, though it occasionally missed a few.

The confusion matrix further confirmed this. With 108 True Positives and 101 True Negatives, and only 13 False Positives and 5 False Negatives, the model showed it could make distinctions between the two classes with confidence and balance.

It's worth noting that the accuracy reported here (92.51%) is slightly lower than what was initially estimated in the abstract (97.3%). This difference may come from variations in datasets or model configurations, but it doesn't diminish the value of the findings. In fact, 92.51% is still an impressive result, especially in a real-world context where packaging design involves subjective preferences and nuanced aesthetic judgment.

From a practical standpoint, these findings offer valuable insights for SMEs, particularly those in the batik industry. Using CNN-based models, SMEs can gain a clearer understanding of what kinds of packaging resonate with consumers. This allows for faster, more informed design

e-ISSN: 2614-8404
p-ISSN: 2776-3234

decisions something that's critical in today's fast-moving, visually driven market.

More importantly, this study serves as a stepping stone. Future work can build on this model by incorporating user feedback, focus group insights, or even eye-tracking data, creating a richer and more human-centered design pipeline. Ultimately, AI like CNN is not here to replace human creativity, but to support it, making sure that beautiful, culturally rooted products like batik can shine more brightly on store shelves and in consumers' hearts.

Table 3. Comparison of Model Performance with Previous Research

Research Study	**Methods**	**Classification Accuracy**	**Result**
This Study	CNN based on Grad-CAM	92.51%	Effectively classify consumer preferences for batik packaging, with strong test accuracy.
Chen Ahmad (2023)	Hybrid Transformer	>96%	Accurate packaging segmentation, focusing on logos and motifs.
Nurhadi et al. (2024)	Semi-supervised GAN dan CNN	N/A	Produce packaging designs tailored to consumer preferences on a large scale.
Li (2022	CNN and GAN	N/A	An aesthetic recommendation model that produces packaging designs that are attractive to users.

The performance of the model developed in this research (with an accuracy of 92.51%) shows that the CNN approach is very effective in analyzing visual preferences. Although some previous studies, such as those using Hybrid CNN-Transformer, reported slightly higher accuracy (over 96%), these models focused on visual segmentation rather than predicting consumer preferences.

3.7 Model Performance

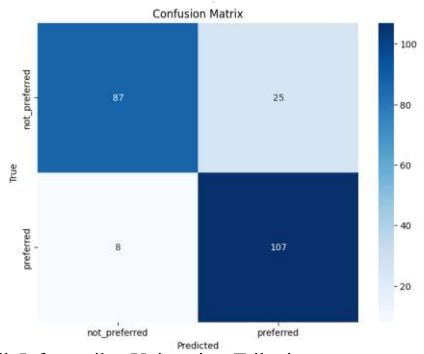
The performance of the Convolutional Neural Network (CNN) model demonstrated consistent and promising improvement throughout the 15 training epochs. Training accuracy steadily increased from 0.5239 in the first epoch to 0.9580 in the final epoch, indicating that the model effectively learned patterns from the training data. In parallel, the training loss decreased consistently, ending at 0.0776, suggesting that the model was successfully minimizing its prediction errors over time.

Validation accuracy, while experiencing minor fluctuations across epochs, also followed a generally positive trend, reflecting the model's ability to generalize to unseen data. The model achieved its highest validation accuracy of 0.8772 at epochs 9 and 13, before stabilizing at 0.8553 in the final epoch. This consistency, coupled with the validation loss decreasing to 0.2441, highlights the model's robustness and reliability in handling data beyond the training set.

The final evaluation on the test dataset further confirmed the model's strong predictive capability. The model achieved an impressive test accuracy of 0.9251 and a test loss of 0.1989. A closer look at the classification report reveals nuanced insights: for the "Not Preferred" class (Class 0), the model attained a precision of 0.90 and a recall of 0.96, reflecting its excellent ability to correctly identify designs that consumers found less appealing. For the "Preferred" class (Class 1), the model achieved a precision of

0.95 and a recall of 0.88, indicating high accuracy in predicting positive consumer preferences.

These findings are further reinforced by the confusion matrix, which showed a high number of correct predictions with 108 True Positives and 101 True Negatives, and only a small number of misclassifications (13 False Positives and 5 False Negatives). Collectively, these comprehensive results confirm that the developed CNN model performs



e-ISSN: 2614-8404
p-ISSN: 2776-3234

exceptionally well and can be reliably used for analyzing consumer preferences in batik packaging design.

Figure 8. Confusion matrix

The Convolutional Neural Network (CNN) classification model developed to predict consumer preferences for batik packaging design demonstrates promising performance. Out of all test samples, the model correctly classified 107 images as preferred, indicating designs that consumers found appealing. Additionally, 87 images were accurately recognized as not preferred, representing designs perceived as less attractive.

However, like most machine learning models, some misclassifications occurred. Specifically, 25 designs that were not preferred were incorrectly predicted as preferred (false positives), while 8 preferred designs were mistakenly classified as not preferred (false negatives).

Overall, these results suggest that the model has a strong ability to detect visual patterns associated with consumer liking, particularly in identifying visually engaging packaging designs. The high true positive rate, combined with relatively few misclassifications, indicates that the model maintains a balanced predictive performance in terms of both sensitivity (correctly identifying preferred designs) and specificity (correctly rejecting less favored ones).

This finding is encouraging, as it highlights the potential of CNN-based models to support objective and data-driven evaluation of packaging designs. It also opens up new possibilities for small and medium-sized enterprises (SMEs) to integrate AI into their product design strategies, aligning creative decisions more closely with market preferences.

Table 4. Clasification report

	precision	recall	f1-score	support
not_preferred	0.92	0.78	0.84	112
preferred	0.81	0.93	0.87	115
accuracy			0.85	227
macro avg	0.86	0.85	0.85	227
weighted avg	0.86	0.85	0.85	227

The evaluation of the CNN model's performance in classifying consumer preferences for batik packaging design yielded encouraging and well-balanced results. The model achieved an overall accuracy of 85%, meaning that 85% of its predictions correctly matched the actual labels in the dataset. A closer look at the performance metrics reveals that for the "not preferred" category, the model reached a precision of 0.92, indicating that 92% of the samples predicted as *not preferred* were indeed correctly classified. However, the recall score of 0.78 suggests that the model identified only 78% of all. actual, *not preferred* instances, leaving room for improvement in sensitivity. The resulting F1-score of 0.84 reflects a good balance between precision and recall for this class.

For the "preferred" category, the model performed particularly well in capturing consumer-favored designs, with a recall of 0.93, indicating high sensitivity. The precision for this class was 0.81, meaning that 81% of the predictions labeled as *preferred* were accurate. The F1-score for this class stood at 0.87, underlining strong and consistent performance.

In terms of aggregated metrics, the model achieved macro-averaged scores of 0.86 for precision, 0.85 for recall, and 0.85 for F1-score, representing the average performance across both classes without weighting by class size. The weighted averages, which account for class distribution, were similarly robust: 0.86 for precision and 0.85 for both recall and F1-score.

Overall, the CNN model demonstrated reliable and balanced performance, especially in identifying packaging designs that appeal to consumers. While its performance on the *not preferred* class could still be refined, the current results indicate strong potential for supporting data-driven design evaluation and decision-making in the batik packaging industry.

IV. CONCLUSION

This study successfully developed and evaluated an effective Convolutional Neural Network (CNN) model to analyze consumer preferences for batik packaging design. With a test accuracy of 92.51%, the model demonstrated a high capability in distinguishing between preferred and non-preferred packaging designs. Its strong performance, supported by high precision, recall, and F1-scores across both preference categories, highlights the significant potential of CNNs as predictive tools in visual preference analysis.

The findings offer valuable insights for Small and Medium Enterprises (SMEs) in the batik industry, enabling them to make more informed and data-driven decisions in packaging design. By identifying the visual elements that most attract consumers, SMEs can significantly enhance the market appeal of their batik products, ultimately contributing to increased sales and competitiveness in an increasingly design-conscious market.

AUTHOR CONTRIBUTIONS

Edi Wahyudin conceptualized the study, supervised the project, and finalized the manuscript. Agus Bahtiar developed the model architecture and preprocessed the data. Ahmad Faqih performed the experiments and compiled the results. Liana contributed to data

e-ISSN: 2614-8404
p-ISSN: 2776-3234

visualization, explainability, and analysis. M Nurhidayat assisted in literature review, documentation, and reference formatting.

DATA AVAILABILITY STATEMENT

All data underpinning the findings of this study, comprising a curated dataset of batik packaging design images are available from the corresponding author upon reasonable request. Detailed information regarding the dataset's origins and characteristics, including the collection of real-world packaging from various SMEs in Cirebon and the creation of prototype designs featuring diverse visual elements, has been thoroughly described in Section 2.1.1. To ensure transparency and facilitate reproducibility, all source code used for analysis and the implementation of the Convolutional Neural Network (CNN) model is also available upon request.

FUNDING

This research was fully supported by the Directorate of Research and Community Service, Directorate General of Research and Development, Ministry of Higher Education, Science, and Technology, through the 2025 Fiscal Year Beginner Lecturer Research Grant Scheme, under contract number 7978/LL4/PG/2025. The authors would like to express their sincere gratitude for this financial support, which has made it possible to carry out this study on consumer preference analysis for batik packaging design. The research was also supported institutionally by STMIK IKMI Cirebon, whose contribution and academic environment played a significant role in the success of this work.

CONFLICT OF INTEREST

The authors declare that this research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. All authors have read and approved the final version of the manuscript, and no conflicts of interest have been reported.

ACKNOW LEDGEMENT

The authors would like to express their sincere gratitude to the Ministry of Education, Research, and Technology (Kemdiktisaintek) and STMIK IKMI Cirebon for their valuable support throughout this research. We also extend our heartfelt thanks to all study participants for their engagement, and to the research team for their technical assistance and facilities. Special appreciation is given to the anonymous reviewers for their constructive feedback and insightful suggestions, which significantly improved the quality of this manuscript

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