

Article

Preserving Songket Heritage Through Intelligent Image Retrieval: A PCA and QGD-Rotational-Based Model

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Abstract

Malay songket motifs are a vital component of Malaysia's intangible cultural heritage, characterized by intricate visual designs and deep cultural symbolism. However, the practical digital preservation and retrieval of these motifs present challenges, particularly due to the rotational variations typical in textile imagery. This study introduces a novel Content-Based Image Retrieval (CBIR) model that integrates Principal Component Analysis (PCA) for feature extraction and Quadratic Geometric Distance (QGD) for measuring similarity. To evaluate the model's performance, a curated dataset comprising 413 original images and 4956 synthetically rotated songket motif images was utilized. The retrieval system featured metadata-driven preprocessing, dimensionality reduction, and multi-angle similarity assessment to address the issue of rotational invariance comprehensively. Quantitative evaluations using precision, recall, and F-measure metrics demonstrated that the proposed PCAQGD + Rotation technique achieved a mean F-measure of 59.72%, surpassing four benchmark retrieval methods. These findings confirm the model's capability to accurately retrieve relevant motifs across varying orientations, thus supporting cultural heritage preservation efforts. The integration of PCA and QGD techniques effectively narrows the semantic gap between machine perception and human interpretation of motif designs. Future research should focus on expanding motif datasets and incorporating deep learning approaches to enhance retrieval precision, scalability, and applicability within larger national heritage repositories.

Keywords: content-based image retrieval (CBIR); cultural heritage preservation; songket motifs; principal component analysis (PCA); rotational invariance



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1. Introduction

The decorative motifs in Malay songket weaving are meticulously arranged to form distinctive patterns that reflect the cultural identity and philosophical values of the Malay community, including gentleness, grace, and adaptability. Nature-inspired designs such as sulur yang lembut (soft tendrils) exemplify the dynamic and flexible spirit of Malay cultural expression [1,2]. These symbolic meanings have spurred scholarly efforts to preserve songket heritage, supporting national initiatives for UNESCO recognition [3].

Information technology plays a crucial role in digitally managing and retrieving archives of songket motifs. However, a significant challenge lies in bridging the semantic gap between low-level image features (e.g., color, shape, texture) and high-level human interpretations of meaning and symbolism [4]. Effective semantic translation mechanisms are required to enhance retrieval accuracy and contextual relevance [5].

Since 2006, Content-Based Image Retrieval (CBIR) techniques have been applied to index songket motifs, yet the accurate retrieval of rotated images remains unresolved. Techniques like Principal Component Analysis (PCA) struggle with rotational invariance. At the same time, recent studies have shown that deep metric learning and rotation invariant feature representations can substantially improve retrieval precision in cultural heritage contexts [6].

This study proposes a CBIR model specifically designed to address the challenges of angular rotation in songket motif retrieval. A mixed-methods approach combining qualitative insights and quantitative evaluation is used to assess the model's effectiveness. The paper proceeds with a literature review (Section 2), methodology (Section 3), results and evaluation (Section 4), and conclusions (Section 5).

2. Literature Review

Image retrieval refers to a computerized process that allows users to search, browse, and access visual data from image databases based on similarity measures [7]. While recent studies recommend a similarity threshold above 85% to ensure relevant retrieval results, other approaches suggest that a threshold of at least 65% can yield acceptable matches in specific domains [7]. Comparative analyses indicate that scores exceeding the top 5 and top 10 generally produce visually meaningful correspondences across varied datasets [8].

Visually similar images often share structural arrangements and object positioning despite differences in scale, color, rotation, and format [6]. While broader similarity tolerances offer users flexibility, excessive redundancy can hinder the efficiency of large-scale image archives [7]. Beyond these issues, researchers have highlighted persistent challenges, including the extraction of representative image features [6] and the development of optimal decomposition and indexing strategies [6]. The similarity threshold θ is automatically updated for each cluster during the learning iterations, ensuring that the threshold adapts to intra-cluster variation and improves retrieval precision [5].

At the core of image retrieval lies the transformation of visual content into structured feature vectors. These vectors enable similarity matching and classification but require robust decomposition and indexing methods to manage the continuous growth of image repositories effectively [6,7]. The initial stage of feature decomposition, a critical technical barrier, is of utmost importance as it directly impacts the precision of indexing and retrieval performance.

2.1. Image Retrieval Challenges

Feature extraction and indexing (including similarity measurement) are widely regarded as the two most crucial factors for content-based image retrieval (CBIR) performance. Deep learning has significantly improved feature representation; however, models still struggle with real-world variability in scale, viewpoint, lighting, resolution, and occlusions [6,7]. These variations complicate the indexing process and hinder generalization to diverse datasets. The efficient management of large image databases remains a significant hurdle, requiring robust and scalable indexing solutions. Ultimately, a retrieval system's effectiveness depends on optimizing both the feature extraction and similarity comparison stages in tandem. If the feature descriptors or distance metrics are not well-aligned be-

tween query and database images, even slight discrepancies can significantly compromise retrieval accuracy [5].

A fundamental obstacle underlying these challenges is the well-known semantic gap between high-level human cognition and low-level machine perception. Humans interpret visual content via abstract concepts (e.g., emotions, cultural symbolism, events), whereas machines rely on numerical descriptors computed from pixels [4]. This semantic gap has long hindered the meaningful retrieval of images according to user intent. Bridging the gap requires translating user queries into machine-readable representations that reflect semantic intent. Promising approaches involve integrating semantic and contextual knowledge into image representations, enabling retrieval algorithms to account for the meaning of content rather than just its appearance. Modern deep learning models partially address this by extracting multi-level features that capture higher-level semantics beyond raw pixel data. For instance, convolutional neural networks can automatically learn hierarchical features (from edges and textures up to object-level concepts) that help connect visual data to semantic labels. Retrieval systems that leverage such enriched features and essentially construct robust classifiers or embeddings from user queries are better positioned to align search outputs with user expectations [6]. Nonetheless, completely closing the semantic gap remains an active research area, as machines still struggle to interpret imagery with the nuance and cultural insight of a human observer.

Content-based image retrieval approaches typically extract a combination of global, local, or spatial features to represent images for indexing and querying. Their effectiveness depends on how well these features accommodate domain-specific characteristics and retrieval objectives, making adaptability a critical determinant of system performance and user satisfaction [5]. Recent work emphasizes tailoring feature extractors to the application domain, for example, modifying neural network architectures to better capture the distinctive patterns of a particular image class. In practice, CBIR systems must often be tuned or learned for the context in which they operate. An effective technique on natural photographs might falter on medical images or, as we discuss next, on culturally significant textile motifs. The ability to adjust and incorporate domain knowledge into the feature representation is therefore crucial for achieving high retrieval accuracy across different datasets [9].

2.2. Domain Specific: Malaysia's Cultural Heritage

Malaysia's cultural heritage, a treasure trove of intangible and tangible riches, is traditionally categorized into two distinct groups. The tangible heritage, comprising physical objects or sites, includes immovable and movable artifacts such as historical structures, tombs, gravestones, and textiles. On the other hand, the intangible heritage, the soul of Malaysia's culture, encompasses the non-physical aspects, including knowledge, practices, and expressions passed down through generations. These are often manifested through oral traditions, performance arts, craftsmanship, social rituals, and similar forms. For instance, traditional textile arts, such as songket weaving, a shining example of intangible cultural heritage, are not just about the finished fabric, but about the skills, symbols, and meanings embodied in the weaving practice. This study explores the intangible cultural heritage of textile art, focusing on the motifs in songket weaving and their preservation and accessibility through image retrieval technology. Notably, researchers have begun exploring digital techniques such as CBIR to study and safeguard songket motif knowledge as part of Malaysia's intangible heritage. Leveraging such technology aligns with the broader goal of protecting cultural patrimony from being lost amidst modernization, reflecting the principle that "history serves as a guide to a nation's civilization" [10]. Through historical

awareness, society can learn to emulate past virtues and avoid repeating past mistakes, underscoring the importance of digitally preserving songket motifs for future generations.

2.2.1. Songket Motifs

Songket Motifs, the fundamental design elements of songket textiles, are not just beautiful patterns but also carriers of the Malay cultural identity. As textile art experts describe, ‘the uniqueness of songket lies in the design philosophy behind its motifs, which serve as expressions of Malay cultural identity’ [1]. Each motif is a unique expression of visual harmony, carrying specific cultural meanings. The preservation of these traditional songket motifs, along with their interpretations, is a crucial task that underscores the importance of digital preservation. Without active efforts to record and disseminate this knowledge, many intricate designs and their stories could be lost in the tide of modernization. Indeed, as songket experts often note, a motif’s value is not only in its visual form but also in the cultural narrative it represents. Digitally archiving motif designs and their descriptions is a responsibility we all share to ensure that this rich intangible heritage endures.

In the context of preservation, it is worth noting the Malay proverb echoed earlier: “History serves as a guide to a nation’s civilization.” By learning about the historical and cultural significance of songket motifs, society is better positioned to appreciate its heritage, emulate the virtues symbolized in these designs, and avoid cultural amnesia. Modern technology, with its ability to make information about motifs widely accessible, plays a crucial role in this process. For example, a digital image repository or motif database allows both designers and the public to explore songket patterns alongside their meanings, thereby reinforcing cultural identity. In recent years, scholars have emphasized the importance of creating such digital archives. Ref. [11] observes that most information on songket is still stored in traditional formats (books, documents, personal collections), which can hinder younger generations from engaging with this heritage. Efforts like developing a songket motif image database with proper metadata are steps toward bridging that gap. By preserving motifs in a digital form, we provide a platform for education and inspiration, ensuring that the knowledge carried by each pattern is not lost, but continually available as “a guide” to future generations.

Consequently, image retrieval studies on songket motifs have gained scholarly interest, particularly in Malaysia and Indonesia, where each country possesses a distinctive tradition of woven motifs. Digitization offers a way to sustain and revitalize interest in these traditional designs. It is a means of safeguarding not just the visual patterns, but the intangible heritage, the cultural knowledge and stories associated with them. The following section reviews how researchers have approached songket motif retrieval and what challenges and findings have emerged from over a decade of studies.

2.2.2. Research in Songket Motifs Retrieval System

Research on CBIR models for songket motifs has been a dynamic field since the mid-2000s, with numerous techniques continually evolving to enhance retrieval accuracy for these intricate patterns. Early work by [12] pioneered the use of image processing to identify songket motifs, achieving notable success by employing simple shape descriptors to characterize the motifs. This early success set the stage for further advancements in the field. Over the years, various feature descriptors and matching strategies have been explored. For instance, ref. [13] reported an F-measure of 91.05% on a dataset of 180 songket images using purely color-based matching approaches. Their system leveraged the distinct color schemes of songket fabrics to retrieve similar motifs. This research [14] extended the color-based method by incorporating sentiment analysis of the motif descriptions; however, once semantic interpretation was added to the pipeline, the overall similarity

score declined to 53%. This drop is likely due to the dual processing of visual features and textual semantics, as integrating these two sources of information proved challenging. This suggests that naïvely fusing color features with high-level sentiment metadata can degrade retrieval performance. The researcher [15] focused on songket motifs originating from Lombok, noting that many of these designs appear visually similar to the untrained eye. They emphasized the need for technological assistance to detect subtle differences in texture and weaving patterns that might distinguish one Lombok motif from another. Their study achieved an F-measure of 86% on 64 images, although the specific techniques for texture feature extraction were not fully disclosed. The challenge highlighted by [15] is a common one: many songket motifs share similar geometric shapes or arrangements, and only fine-grained differences (for example, in weaving texture or thread orientation) separate them. Identifying these subtleties is difficult without automated analysis. Encouragingly, recent work has begun applying deep learning to this problem. For example, ref. [16] developed a ResNet-based classifier for Palembang songket motifs, achieving roughly 80% accuracy in distinguishing motif classes.

This underscores the potential of advanced AI techniques in motif recognition, while also indicating areas for improvement in discerning the subtle differences among similar motifs [16]. As these deep learning models advance, they are expected to capture texture nuances more effectively and enhance the identification of similar motifs. The future of CBIR models for songket motifs looks promising, with deep learning models set to significantly elevate motif recognition. Notably, some researchers have questioned the relevance of certain low-level features in understanding songket motifs. Ref. [12] argued that color and texture make only a marginal contribution to the semantic understanding of songket designs. They argue that the cultural significance of a motif is primarily embedded in its shape and form. In other words, the contour and structure of a motif (floral vs. geometric, etc.) carry more weight than the specific colors used. Recent discoveries in image retrieval support this viewpoint: studies have found that images with highly intricate shapes and textures can pose challenges for retrieval systems, often resulting in lower accuracy compared to images with simpler, more distinct color patterns [10]. For instance, a report states that in an image dataset of traditional fabrics, items with intricate multi-pattern motifs had lower retrieval accuracy than those primarily differentiated by color or broad shapes.

This highlights the significance of utilizing advanced shape descriptors or learned features in songket motif retrieval systems, ensuring that the audience remains well-informed about the current state of research. While algorithms can easily match color and basic texture, capturing the semantic essence of a motif such as a specific floral design that holds cultural significance in Malay tradition poses a challenge. This reinforces the notion that sophisticated shape descriptors or learned features, which prioritize form, are essential for effective songket motif retrieval. Simple color histograms or general texture metrics may not be adequate for distinguishing motifs in a culturally relevant manner.

Ref. [14] pointed out the considerable limitations of text-based retrieval models for songket-related information, noting that users, particularly non-experts, often struggle to formulate suitable search queries when attempting to describe a motif in words. For instance, someone searching for a specific songket pattern might not know the motif's name or the appropriate keywords, leading to ambiguity in textual descriptions. To address this issue, ref. [14] proposed an example-based visual query approach: rather than typing in keywords, users can provide an example image of the motif they are seeking. This method yielded a 75% relevance rate, with 9 out of 12 test queries producing relevant images. While this performance demonstrates the potential of visual queries, the study had its limitations, notably evaluating only 12 queries from a collection of 450 images. This raises crucial

questions about how the system would scale or perform with unseen motifs. Additionally, the paper did not detail the specific shortcomings of text-based retrieval that their approach aimed to overcome. These findings resonate with broader observations that keyword-based searches often fail to capture the intricate visual attributes of motifs.

In the context of songket, a user might search for “flower motif with gold thread,” a query that could correspond to numerous patterns. Visual search, on the other hand, allows the system to use the motif’s appearance directly. However, ref. [14] did not significantly enhance prior retrieval accuracy benchmarks, indicating the need for further refinement of example-based search techniques. This also underscores the importance of comprehensive evaluations; using only a small subset of queries can present an overly optimistic view of a system’s effectiveness. Future studies should test on larger and more varied query sets to truly gauge the benefits of example-based retrieval. Ref. [17] noted that general users often struggle to distinguish among similar songket motifs due to the visual complexity of the motifs. Songket designs can be densely packed with details, and without guidance, non-experts may struggle to distinguish patterns or identify a motif’s defining features. While ref. [17] did not focus on retrieval, it made a significant contribution to image preprocessing for motif analysis. They enhanced motif imagery by applying Canny edge detection to delineate motif boundaries clearly, and then used PCA (Principal Component Analysis) for dimensionality reduction and KNN (K-Nearest Neighbors) for classifying motifs into types. Their pipeline cleaned up the images and reduced noise so that the motifs’ shapes were more pronounced before attempting to classify them. This approach, similar to that of [18], places significant emphasis on preprocessing workflows. Ref. [19] had earlier developed an automatic cropping technique to isolate the motif from its background in scanned songket images, a necessary step in scenarios that still relied on hardcopy images of songket fabrics (e.g., photographs or scans from books). In many practical cases, motifs may appear in images with extraneous backgrounds or multiple motifs in a single frame, so isolating the specific motif of interest is crucial for accurate retrieval. Traditional archives of songket patterns, if non-digital, often require such preprocessing when being digitized. Refs. [17,19] efforts in edge detection and cropping underscore the ongoing need for robust image preprocessing in motif retrieval systems, particularly as older physical collections are transitioned into digital databases [17]. As image acquisition improves (e.g., high-resolution direct digital photography of textiles), some of these steps may be simplified; however, they currently remain an important part of the pipeline for songket CBIR. Ref. [18] reported an impressive 98% image similarity score using a CBIR system based on a Backpropagation Neural Network. Their system was trained to recognize a set of known motif patterns and performed very well on those, indicating the power of even relatively early neural-network approaches for this task. Ref. [17], using their enhanced-images approach with PCA+KNN, achieved 91.67% classification accuracy across five motif types. Despite these high accuracy levels, it is essential to note that both studies were narrowly scoped and focused on limited sets of motif categories. As mentioned, they devoted much effort to preparing the data (cropping, denoising, etc.). In other words, their contributions lie more in data preparation and demonstrating feasibility on small scales, rather than in fundamentally new retrieval algorithms.

In summary, across the reviewed studies, there is a shared consensus that public knowledge regarding songket motifs remains limited among many people, and even within Malaysia, they are unable to identify or name specific motif designs readily. It is further emphasized that designers often encounter challenges in conceptualizing new patterns due to the absence of easily accessible digital motif archives [12]. In the traditional process, a songket designer might have to flip through books or physical samples to find inspiration or ensure a new design does not inadvertently duplicate an existing one. A digital retrieval

system encompassing both classic and contemporary motif collections could significantly streamline this process. By quickly referencing an online catalog of motifs, designers could re-use or adapt heritage designs with confidence. Ref. [20] echoed this idea, noting that a comprehensive image archive of motifs would support both preservation and creative innovation. Preserving and innovating traditional designs is a responsibility that everyone in the field should uphold. An instantly searchable database of existing patterns can significantly aid designers in rapidly producing new designs.

The application of digital techniques enables designers to create new motifs while retaining traditional elements, thereby offering creative freedom and technological support in motif development [21]. This AI assistance, however, is not meant to replace human creativity but to enhance it, providing a wealth of inspiration and information that can be used to create unique and culturally significant designs. Despite songket's cultural importance, ref. [22] found that most songket-related websites prioritize commercial promotion (selling fabrics) over educational content about the motifs' heritage. This means public access to information about the symbolic meanings and classifications of each motif is limited. Consequently, many individuals remain unfamiliar with even the names of songket motifs, let alone their more profound significance [2]. Similarly, it has been observed that knowledge about songket weaving heritage is still primarily disseminated through conventional media, such as books, academic theses, and documentaries. These traditional channels, however, no longer effectively engage the broader public, especially younger generations accustomed to digital and interactive content. The urgency of the shift towards digital media for cultural heritage outreach is apparent. Studies on intangible heritage have noted that merely presenting information in static forms leads to limited audience engagement.

There is a pressing need for interactive platforms, such as mobile apps, online databases, or even gamified experiences, that can attract and educate users compellingly about motifs. The transition to digital formats is not just a trend but a necessity. Recent research has highlighted issues such as variable content quality and potential misrepresentation of cultural context in digital media. However, these challenges should not deter us from embracing digital platforms. Instead, they should serve as a reminder of the crucial responsibility we have in maintaining the authenticity and cultural context of songket motifs in the digital realm.

If not performed carefully, digitizing heritage can lead to distorted interpretations (e.g., motifs shown without explanation of their meaning, or designs taken out of their cultural context). This highlights the crucial importance of collaboration between technologists and cultural experts in developing digital archives and tools. The task of preserving and promoting songket cannot be undertaken by a single group or discipline. It requires a concerted effort and a deep understanding of the cultural and historical significance of songket. Leveraging technology is undeniably essential to support initiatives by the Department of National Heritage in sustaining songket as part of Malaysia's intangible cultural heritage. This art form received formal recognition by UNESCO in 2019. The UNESCO inscription of "Songket Malaysia" on the Representative List of Intangible Cultural Heritage of Humanity has increased both international and local interest in this textile tradition. Such recognition not only honors the weavers and communities behind songket but also places an impetus on Malaysia to preserve and promote this heritage. It opens up opportunities to educate the public, attract cultural tourism, and even inspire contemporary fashion designers. Indeed, UNESCO acknowledgement can strengthen Malaysia's appeal to cultural tourists and may contribute to national economic development through heritage-related activities. However, to fully realize these benefits, there must be accessible knowledge platforms about songket. As noted, simply having the art form recognized is not enough; the public needs engaging ways to learn about and experience it in its early works. This is

where digital technology plays a pivotal role. Expanding research and cross-disciplinary collaborations that combine digital technologies with cultural heritage preservation could foster greater public engagement and awareness. For example, augmented reality apps might allow users to virtually “try on” songket patterns, or interactive websites could display the evolution of specific motifs over time and geography. Such initiatives align with global trends, as many organizations are striving to overcome the traditionally limited audiences of heritage transmission by integrating intangible culture with digital media and commercial platforms.

There is momentum worldwide to incorporate traditional arts into modern experiences (gaming, fashion shows, online exhibitions) to keep them alive and relevant. UNESCO’s recognition of songket also comes with the responsibility to safeguard it, which means not only protecting the practice of weaving but also ensuring that the knowledge (weaving techniques, motif meanings) is passed down. Modern digital archiving and retrieval systems can be a cornerstone of that safeguarding process. Beyond implementing a CBIR-based retrieval and archival platform for songket motifs, sustained technological innovation in this domain remains critical. Challenges will continue to evolve—from improving recognition accuracy and speed to enriching metadata (e.g., linking motifs to their stories) and enhancing user interaction. The urgency and importance of these ongoing efforts cannot be overstated. We must also address obstacles, such as ensuring the authenticity of information and encouraging users to adopt these new tools.

In essence, maintaining songket’s legacy in the digital age is an ongoing endeavor. By continuously enhancing the interdisciplinary approach between technology and cultural heritage, we can better support the conservation of songket motifs and ensure that this Malaysian art form not only survives but also thrives in the years to come [23].

2.3. Image Retrieval Model Comparison

The purpose of comparing existing models is to design and develop a new image retrieval system for songket motifs by referencing key structural components. The following section outlines previous innovations in image retrieval models that serve as foundational references for this study.

2.3.1. Bag of Visual Words Model

The Bag of Visual Words (BoVW) model, a crucial framework in the field, is widely used for assessing and matching sets of visual words between a query image and stored images [24]. In this approach, the features extracted from a query image are compared against a predefined visual vocabulary to identify relevant matches, thereby facilitating effective image retrieval. The model transforms local feature descriptors into discrete or binary representations to support the semantic interpretation of visual content, particularly in the analysis of local spatial features [17]. Its role in image retrieval is of utmost importance and significantly contributes to the advancement of the field.

Typically, BoVW involves three main stages: (1) extraction of local spatial features, (2) measurement and comparison of these features against the database vocabulary, and (3) transformation of matched features into visual word tokens. This process also supports scene classification, where each image is categorized according to its unique combination of visual word representations. The evaluation of associated word meanings further refines the system’s semantic understanding of image content.

While the Bag of Visual Words (BoVW) technique has proven effective for analyzing local spatial features within images [17], it does have its limitations. Notably, its performance tends to decline when applied to larger image datasets due to the increased computational demands of feature extraction and matching [6]. Additionally, BoVW does not account

for patch-level correspondence between query and reference images, a critical component for constructing accurate image representations that serve as an intermediary language for system-level semantic understanding [25]. These limitations underscore the need for further research and development in the field of computer vision.

2.3.2. Min-Hash Model

The Min-Hash technique, initially developed for text-based retrieval systems [26,27], is a remarkably versatile tool that can bridge the semantic gap between datasets by computing average variable values [28]. Its potential applications are vast and intriguing. AltaVista search engine adopted this method as early as 1995, using Jaccard similarity to measure overlap between data groups. In image retrieval, the Jaccard distance is applied to compare query and stored images based on semantic tags, object structures, and foundational image features [29]. Semantic labels are converted into matrix form for processing.

Representing images using matrix structures enables more efficient retrieval by measuring similarity based on numerical values derived from image data. Although text-based numerical representations are considered adequate, they often struggle to accurately match the modified versions of original image data [29]. This model is a refined Min-Hash model, which incorporates significant enhancements such as improved feature extraction, more accurate similarity measurement, and a more robust indexing approach. These improvements pave the way for the future potential of the Min-Hash model in image classification and indexing processes.

This enhancement focuses on improving the effectiveness of image matrix value reordering for better classification and indexing [30,31].

2.3.3. SVD-SIFT Model

The SVD-SIFT model, a powerful solution to the challenges of feature extraction from user-modified images [32], offers significant benefits. This hybrid approach, combining SVD for detailed matrix decomposition with SIFT, effectively detects image alterations such as rotation, scaling, format changes, and complex content edits, thereby enhancing the quality of image processing.

While SIFT's local image feature identification using binary pattern recognition [6,33] is effective, it comes with high computational costs, leading to slower retrieval performance [34,35]. Recognizing this, ref. [32] suggests the integration of complementary techniques to accelerate feature extraction, highlighting the importance of a holistic approach to image processing.

The SVD-SIFT process begins with SIFT-based feature extraction and is then followed by SVD to streamline the computation of similarity. However, SVD itself requires multiple processing stages, which can potentially reduce retrieval efficiency in cases involving high feature complexity [36].

2.3.4. Visually Salient Riemannian Space Model

The Visually Salient Riemannian Space (VSRs) model, introduced by [37], was developed with the potential to address challenges arising from the uncontrolled proliferation of redundant image and video data shared by users. Inconsistent manual tagging and widespread editing—such as compression, rotation, cropping, and geometric transformations—further complicate database classification and retrieval [38].

To overcome these issues, VSRs improve two key components: (1) efficient feature decomposition to accelerate similarity matching without compromising image quality, and (2) enhanced comparison of query and stored images for robust visual matching. The integration of Independent Component Analysis (ICA) further supports rapid feature comparison during similarity evaluation.

Independent Component Analysis (ICA) is a valuable tool for computing image content structures during similarity matching. However, its multi-phase processing framework, which involves mapping and aligning structural attributes across images, presents challenges in clearly defining image features [39]. To overcome these constraints, researchers have explored hybrid models that integrate ICA with other techniques to enhance the effectiveness of image feature decomposition [37,39].

2.3.5. Fourier–Mellin Transformation Model

Image feature decomposition in general image retrieval models faces challenges in accurately extracting key characteristics essential for indexing similar images. Effective indexing requires image features that are both unique and discriminative, as these characteristics play a crucial role in differentiating and categorizing images. According to [40], significant difficulties arise when processing images that have undergone geometric transformations such as rotation, scale variation, and translation [41]. To address this, the Fourier–Mellin Transform (FMT) model is employed to improve robustness against such transformations. The FMT-based approach involves two key phases: (i) extraction of edited image features for comparison and (ii) implementation of a log-polar transformation to enable image matching via binary image representation. This transformation converts Cartesian coordinates (x,y) into a binary format, facilitating more efficient image indexing [42].

2.3.6. Shape-Based Image Retrieval Model

Shape-based image retrieval measures the similarity between structural features of shapes within an image, which are fundamental to identifying objects [43,44]. However, the field is not without its challenges. Many image retrieval systems face difficulties in decomposing, measuring, interpreting, and detailing shape-based features, adding a layer of complexity to the process. Two main stages facilitate similarity matching between queries and stored images: first, shape feature decomposition, and second, similarity distance measurement.

Shape-based retrieval techniques are generally categorized into two approaches: region-based and contour-based. Region-based features, which represent the entire image area, play a crucial role in texture analysis. This involves measuring matrix arrangements to differentiate between object regions [45]. However, segmentation remains a challenge when similar tones (e.g., white and light indigo) occur across object boundaries, limiting the accuracy of feature extraction.

The model proposed by [12] comprises two main modules: a database module and a retrieval module. The database module encompasses image preprocessing tasks, including segmentation, noise reduction, and ground truth determination. It also integrates five key shape descriptors: elongation, rectangularity, density, convexity, and solidity for comparing shape-based similarities.

2.3.7. Palembang Motif Image Retrieval Using Canny Edge Detection, PCA, GLCM, and KNN Techniques

The image retrieval study for songket Palembang motifs employed a combination of Canny edge detection, PCA, GLCM, and K-Nearest Neighbor (KNN) techniques, each serving distinct purposes. The Canny edge detector was used for noise control in motif data through four steps: (i) smoothing image edges to reduce noise, (ii) identifying gradients, (iii) suppressing non-maximum gradients, and (iv) linking edge pixels. Subsequently, the PCA method was applied for feature decomposition, while the Gray Level Co-occurrence Matrix (GLCM) was used for indexing existing features. KNN facilitated the

indexing of new features and computed similarity distances between query images and the stored dataset.

The reviewed studies primarily focused on full songket Palembang textiles without addressing specific motifs or rotational transformations. Among seven image retrieval models, five used general images as their domain, while only two specifically explored cultural heritage images, such as songket motifs. Two initial models employed text-based features: one used Bag-of-Visual-Words (BoVW) to extract text features in binary form, while the other applied Min-Hash to analyze textual and color features in matrix form. While text-based approaches remain relevant as they allow users to specify image characteristics, they are not without their limitations. For instance, semantic gap issues persist due to inefficiencies in manual tagging and delays in interpretation [45,46].

Three other models focused on shape-based features, influenced by the variability of objects within images. The SVD-SIFT model emphasized image rotation, while the VSRs model targeted geometric editing, such as cropping and rotation. Another model analyzed combined shape descriptors (e.g., irregularity, convexity, density, rectangularity, solidity). A separate model investigated motion-based image retrieval, addressing scale and size changes in videos. Ref. [17] presented a recent model related to songket, but it focused on matching entire textile structures rather than individual motifs.

The analysis reveals that effective image retrieval systems require two integrated modules: a database module (covering motif categorization, preprocessing, feature extraction, and motif image storage) and a retrieval module (handling query input, feature decomposition, similarity measurement, and result display). Another study emphasized preprocessing integration but did not address rotational transformations of motifs [12]. Furthermore, earlier studies gave limited attention to data collection and ground truth determination. The need for better data validation and ground truth protocols is urgent. While ref. [47] briefly mentioned classification, detailed protocols were lacking. Most researchers relied on general online datasets, often without rigorous validation.

2.4. Discussion

The evolution of content-based image retrieval (CBIR) systems for songket motifs has been progressive yet fragmented. Researchers have employed a range of techniques, from basic color matching to more complex hybrid models. While these individual contributions have improved retrieval accuracy, the field still lacks a cohesive framework for preserving and retrieving cultural motifs. This highlights the current state of the field and the direction for future research.

Studies such as [13,17] demonstrate that edge detection and PCA-based classification yield high similarity scores, affirming the effectiveness of these methods in pre-processing and feature compression. Nonetheless, their applicability is limited by the narrow scope of motif representation and the lack of consideration for rotational variations, which is an essential aspect when dealing with textile heritage, where motifs may be presented in multiple orientations across fabrics.

Furthermore, the inclusion of sentiment analysis [45] and shape-based descriptors [12,43] has introduced semantic richness but has also diluted system precision due to increased computational complexity and user interpretation variability. This tension between semantic depth and system efficiency highlights a central challenge in heritage CBIR design: striking a balance between cultural interpretation and algorithmic performance.

The comparison with established models such as Bag-of-Visual-Words (BoVW), Min-Hash, and Fourier–Mellin Transform (FMT) reveals their limitations. While these frameworks excel in general image retrieval tasks, they fall short in handling the nuanced

structural features specific to songket motifs. This underscores the necessity for innovation in the field of CBIR systems for songket motifs.

Recent advances, including the integration of SVD-SIFT and VSR models, attempt to address distortions such as scale, rotation, and compression. However, these models require significant computational overhead, which limits their scalability across extensive cultural archives. Moreover, their reliance on multi-phase decomposition often results in semantic drift, which is problematic when preserving the authenticity of heritage images.

Crucially, the absence of standardized datasets and validation protocols across studies presents a barrier to meaningful cross-comparison and benchmarking. This urgent need for large-scale, annotated heritage datasets with ground truth validation that capture motif diversity across regions and weaving techniques is a pressing concern that must be addressed.

In this context, the proposed PCA-QGD-based model emerges as a beacon of hope, making a meaningful contribution by explicitly addressing rotational invariance—a key limitation in earlier works—and by integrating metadata-driven pre-processing, structural feature normalization, and multi-angle matching mechanisms. This holistic architecture not only enhances precision in motif classification but also supports interoperability with national digital archives, aligning with UNESCO’s mandate for the preservation of digital heritage.

3. Methodology

The proposed image retrieval framework extends the traditional architecture of information retrieval systems, which is typically composed of two primary modules: the indexing component and the query component. The indexing component organizes extracted features into structured data for efficient storage and access, while the query component enables user-driven searches that generate ranked retrieval results from the indexed database. For semantic image retrieval, however, an additional feature decomposition component is essential. This module performs preprocessing and transformation of raw image data into structured feature vectors, ensuring that motifs are represented in a form suitable for consistent comparison, classification, and semantic interpretation.

To operationalize this framework, a songket motif image database was constructed, serving as the foundation for indexing, querying, and feature decomposition. The dataset comprises 413 original images augmented with 4956 synthetically rotated variants (12 rotations per image) to increase intra-class variability and enhance retrieval robustness. Each entry in the database integrates three layers of information: (i) the visual data (image file), (ii) technical metadata (e.g., FileName, FileModDate, FileSize, Format, FormatVersion, Width, Height, BitDepth, ColorType), and (iii) semantic annotations describing cultural context, including motif name, cloth section/placement, and associated philosophical meaning. Importantly, technical metadata are automatically extracted through the InitializeMetadataStructure routine (Figure 1), ensuring systematic integration of image attributes with semantic knowledge. This unified structure directly supports the framework’s three components, indexing, querying, and feature decomposition, and thus enables hybrid (visual + semantic) retrieval.

Semantic annotations are curated by domain references and artisan interviews, as shown in Table 1. This integration allows the proposed model to exploit both content-level features (pixels) and context-level descriptors (placement and philosophy) during retrieval and analysis.

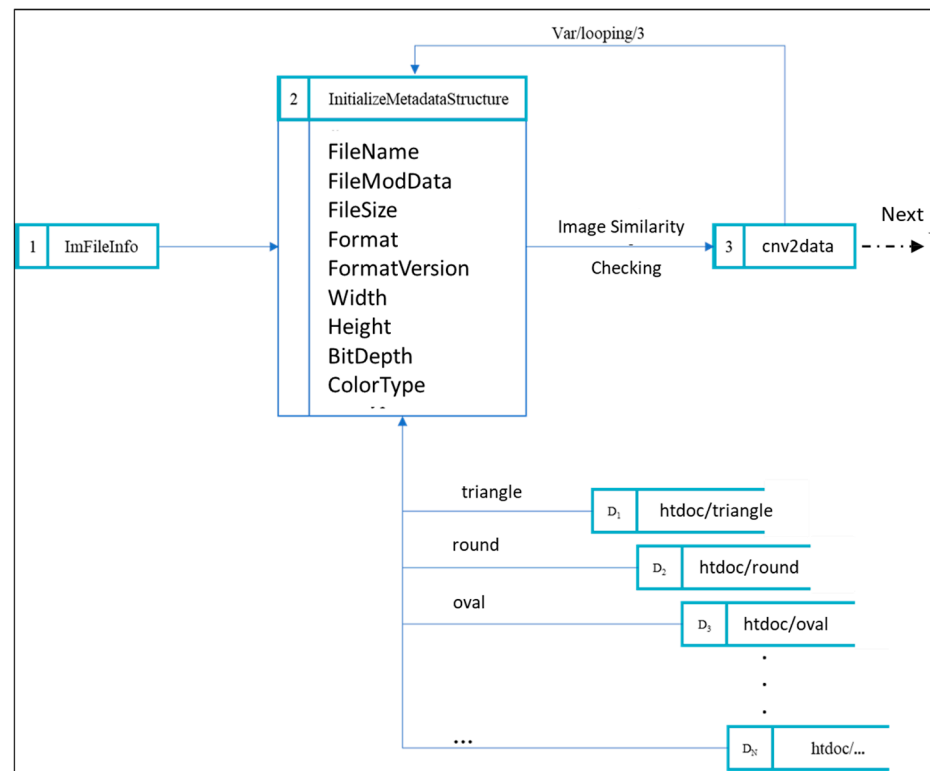


Figure 1. Details of the ingestion workflow that standardizes image properties and validates integrity before indexing. By unifying technical metadata (Figure 1) and semantic knowledge (Table 1) within a normalized schema, the system supports metadata-aware preprocessing, culturally grounded annotation, and hybrid (visual + semantic) retrieval.

Table 1. Presents representative motifs by cloth section and their cultural symbolism. For example, Bunga Ketola/Petola, traditionally placed at the head of the cloth, signifies loyalty between the people and their king; Bunga Anggerik/Orkid on the body represents feminine delicacy, refinement, and the nurturing role of mothers; Bunga Corong along the edges conveys harmony between humankind and divine creation; and Bunga Bebaling in scattered arrangements symbolizes the axis of the human life cycle.

Songket Cloth Section	Songket Motif	Motif Songket Images	Philosophy
Head of the cloth	<i>Bunga ketola/Petola</i>		Symbolizes the loyalty between the people and their king.
Body of the cloth	<i>Bunga Anggerik atau Orkid</i>		Represents the character of a woman who is delicate and requires nurturing with noble values and cultural refinement, as women are the mothers of households who will shape the future generations of the ummah.
Cloth edge/Side panel/Foot of the cloth	<i>Bunga corong</i>		Symbolizes the harmony between human beings and the natural world created by the Divine.
Scattered arrangement	<i>Bunga Bebaling</i>		Reflects the axis of the life cycle of a human being.

3.1. Data (Pre-Processing)

Stage I involves data selection from the image database, beginning with size matching between query and stored images. Each image is converted from integer to double precision to enable floating-point representation, scaled between 0 and 1 (from an original range of 0 to 255), allowing size normalization ($M1/M2$) to proceed. If image dimensions are inconsistent, an error message “Image size mismatch” is displayed. Figure 2 presents the corresponding algorithm.

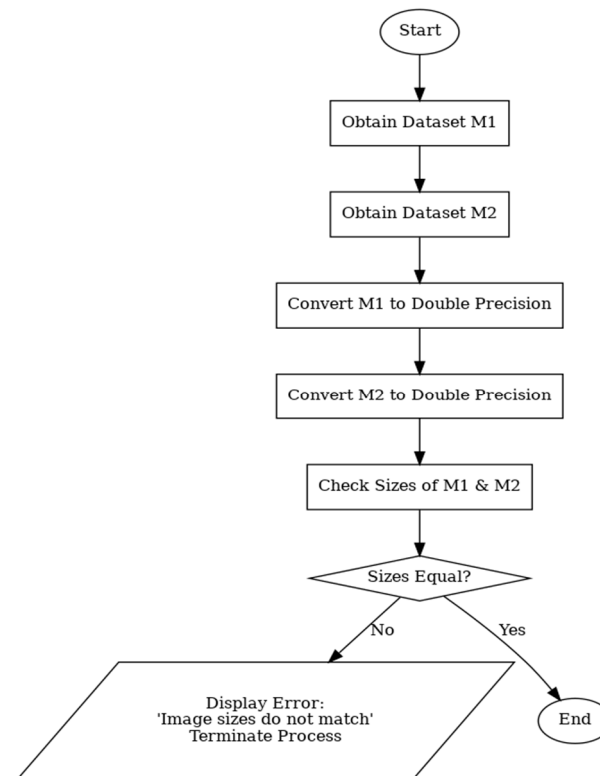


Figure 2. Data retrieval algorithm for training and testing sets.

3.2. Model Development Process

This section details Stage II: Model Development. Scaled images from Stage I are processed using Principal Component Analysis (PCA) for feature extraction.

Stage II—Part I: Principal Component Analysis (PCA) involves six key steps:

1. Computing the covariance matrix from the scaled image data.
2. Calculating eigenvectors and eigenvalues. The first eigenvector is aligned through the centroid to determine the best-fit line, while the second represents less significant variance.
3. Reducing dimensionality by selecting the highest eigenvalue to represent the principal component, with eigenvectors ranked from highest to lowest priority.
4. Deriving PCA scores using Equation (1).
5. Classifying the PCA scores.
6. Eigenvectors and eigenvalues, represented as X , are passed to Stage II—Part II for similarity matching.

Eigenvalue computation involves resizing the original image and applying a similarity-based algorithm using sine and cosine functions $(s_j \cdot \sin h_j - s_i \cdot \sin h_i)^2$. The symbols are defined as follows: S represents the spatial coordinate values of the image pixels (with subscripts i and j denoting two different pixel positions or feature points), while h denotes the angular orientation (in radians or degrees) associated with each spatial coordinate,

used to measure rotation alignment. For example, $s_j \cdot \sin h_j$ corresponds to the projection of point j along the sine of its angular orientation. By computing the difference between such projections, the algorithm captures rotational variations and ensures more accurate similarity measurement.

Typically, the number of principal components (K) is less than or equal to the number of original image dimensions (M). Image normalization plays a key role in reducing dimensional variance, aligning variations across images within the same group, and minimizing noise for improved feature extraction. This process, based on PCA, uses mean value computation to normalize structural properties within the image [48].

Normalization ensures consistent similarity matching among images that share structural features but differ due to edits such as rotation [49]. Figure 3 illustrates two core steps in the rotation measurement process:

1. A rotated object derived from the original image.
2. Alignment of rotated objects of differing sizes for consistency.

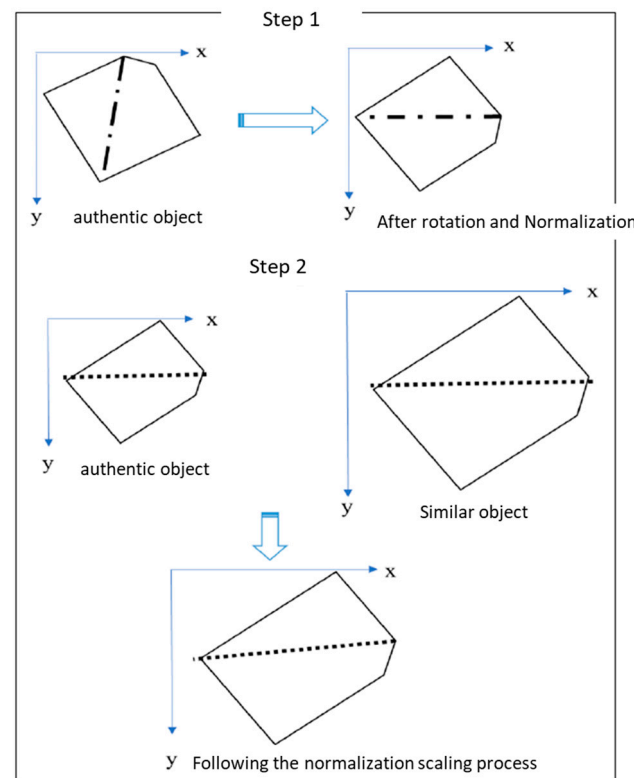


Figure 3. Detailed procedure for image rotation measurement within the developed model.

Overall, normalization aids in structurally aligning similar objects with variations in size and rotation for accurate similarity comparison.

In this study, the eigenvalues corresponding to each songket motif image were calculated based on the covariance matrix constructed from the image data. The covariance formula, presented in Equation (1), defines the covariance between two image variables, denoted as $cov(x, y)$, using sampled image data. The variables a and b were randomly assigned according to the covariance matrix formulation proposed by [50], as detailed in Equation (1).

$$cov(a, b) = \frac{1}{N-1} \sum_{i=1}^N (a_i - \mu_a) * (b_i - \mu_b) \quad (1)$$

In Equation (1), μ_a and μ_b represent the mean values of variables a and b , respectively. The asterisk (*) signifies a complex operator applied to the observed variable data, and it represents the covariance operator as applied in the covariance matrix formulation. The covariance matrix capturing the relationship between the two randomly assigned variables is calculated according to the formulation specified in Equation (2).

$$C = \begin{pmatrix} \text{cov}(a,a) & \text{cov}(a,b) \\ \text{cov}(b,a) & \text{cov}(b,b) \end{pmatrix} \quad (2)$$

In the covariance matrix, variable a comprises columns that are randomly selected through system-driven observation. Each column contributes proportionally to the covariance value, which is represented as Equation (3).

$$C(i, j) = \text{cov}(A(:, i), A(:, j)). \quad (3)$$

As described by [49], the interpretation of the covariance function $\text{cov}(a, b)$ depends on the input type:

1. When a and b are vectors of equal length, the output is a 2×2 covariance matrix.
2. When a and b are observation matrices, they are reshaped into vectors using $\text{cov}(a(:), b(:))$, which requires identical dimensions.
3. When a and b are scalars or empty arrays, the function returns either a 2×2 zero matrix or a NaN block, respectively.

The eigenvalues computed via PCA must account for the dimensional space of the image, where each image is treated as an $N \times N$ matrix (for example, 256×256 pixels, totalling 65,536 elements). Processing high-resolution images across large datasets imposes considerable computational demands, which can delay retrieval performance [51] and reduce user confidence in the system [52].

In Figure 4, each column of the image matrix corresponds to one motif image. In the higher-dimensional space, each column consists of 55,696 pixel values (236×236), while in the lower-dimensional space, after PCA-based reduction, each column is compressed into 10,000 values (100×100). This reduction enables efficient decomposition, selection, and normalization for retrieval. This dimensionality reduction, integrated into the PCA covariance computation (Equation (3)), is essential for efficiently extracting the core structural features of songket motif images [53].

The eigenvectors and eigenvalues are represented by the symbol X , which is used for the similarity matching and comparison process in Part II.

The X values obtained from Part I serve as reference points in the Quadratic Geometric Distance (QGD) technique, which is used to compute similarity and dissimilarity between query and stored images. The QGD formula, as proposed by [54], is presented in Equation (4).

$$ax^2 + bx + c = 0 \quad (4)$$

In this context, the symbols a , b , and c represent coefficient values, which are real numbers associated with the variable x , whose value is initially unknown. These coefficients from the initial equation are embedded into Equation (5) for graph construction and computation.

$$X_{1,2} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a} \quad (5)$$

Figure 5 illustrates the flowchart outlining the key steps in the Quadratic Geometric Distance (QGD) measurement process, which includes Phase II (Similarity Matching Phase), Phase III (Rotation Handling Phase), and Section II (QGD Computation Module) as integral parts of the overall workflow.

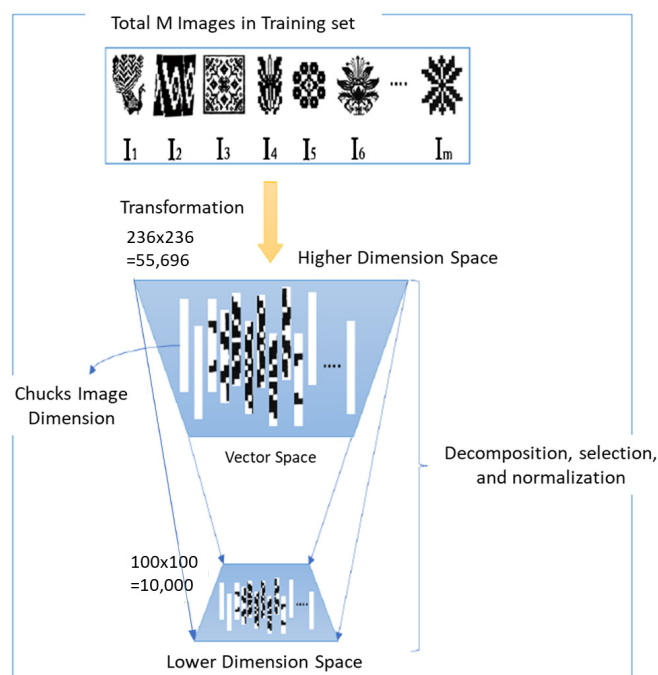


Figure 4. The image decomposition and dimensionality reduction processes carried out using the Principal Component Analysis (PCA) technique.

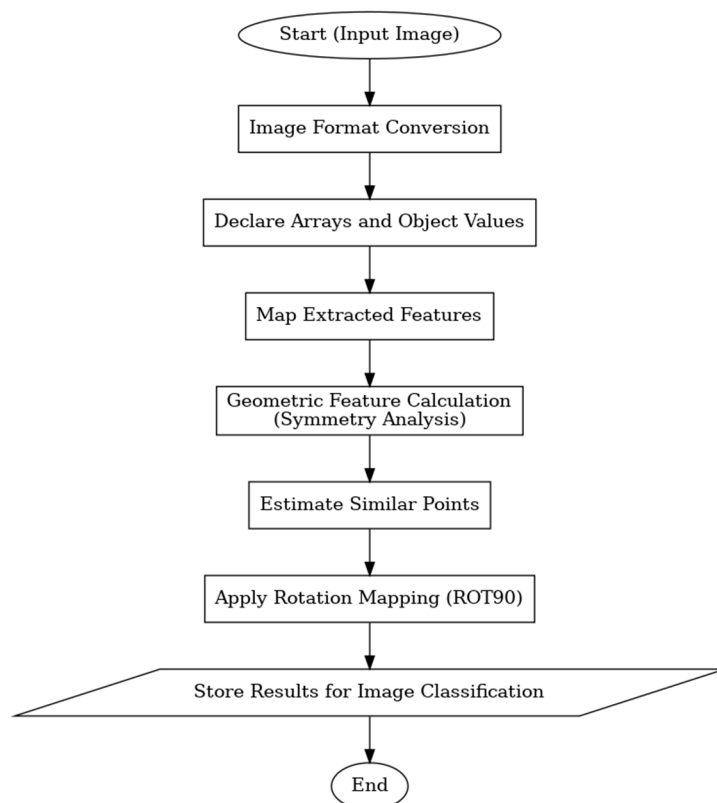


Figure 5. Flowchart outlining the Quadratic Geometric Distance (QGD) measurement process. The process begins with input image preparation through format conversion, followed by declaration of arrays and object values. Extracted features are then mapped and analyzed through geometric feature calculation (symmetry analysis). Similar points are estimated and subsequently refined by applying a rotation mapping (ROT90) to ensure rotation invariance. Finally, the results are stored for image classification, enabling accurate retrieval performance.

1. Image format conversion;
2. Evaluation of image features extracted;
3. Declaration of arrays;
4. Declaration of image objects;
5. Geometric feature calculation through symmetrical analysis;
6. Matching the closest points based on feature similarity;
7. Estimating binary points for precision matching;
8. Storing the estimated matches for image classification.

During the second phase, the PCA output X (database image features) and the query image X_1 are both transformed from the RGB color space into HSV using the `rgb2hsv()` function. This produces $HSVmap$ (for database images) and $HSVmap1$ (for the query image). The use of HSV is important because it separates color information into three perceptually meaningful channels: Hue (H), Saturation (S), and Value (V).

The similarity between the query and each database image is then computed using the `quadratic1()` function. This function decomposes the comparison into three distance measures: D_1 (Hue similarity), D_2 (Saturation similarity), and D_3 (Value similarity). Each distance value reflects how closely the query image matches the corresponding channel of a database image.

The system iterates through all images in the database. For each comparison, the values of D_1 , D_2 , and D_3 are stored in separate result arrays (`resultValues1`, `resultValues2`, `resultValues3`), and the image filename is recorded in `resultNames`. This structure ensures that every computed similarity score can be directly traced to its corresponding motif image.

Three spatial descriptors, $s1s_1s1$, $s2s_2s2$, and $s3s_3s3$, are then applied to compute the quadratic form for each channel. The QGD values are calculated using the following expressions in Equation (6):

$$D_i = \frac{\sqrt{S_i^T A s_i}}{10^8}, \text{ for } i = 1, 2, 3 \quad (6)$$

In Equation (6), D_i denotes the distance value, or similarity score, computed for the i -th HSV component, where D_1 , D_2 , and D_3 correspond to similarity in the Hue, Saturation, and Value channels, respectively. The term s_i represents the feature vector extracted from the i -th HSV channel of the transformed image, capturing pixel-level attributes for that channel, while S_i^T is its transpose, allowing the quadratic form computation. Matrix A , referred to as the similarity matrix or quadratic geometric distance matrix, encodes the pairwise relationships between the HSV representation of the query image ($HSVmap1$) and that of a database image ($HSVmap$). The quadratic form $S_i^T A s_i$ thus measures the weighted similarity between feature vectors, taking into account both their magnitude and directional correlation. Taking the square root ensures that the distance value remains normalized and positive, while the denominator 10^8 serves as a scaling factor to control the numerical range of the results, improving stability and comparability across images without altering their relative similarity. The computation is performed independently for $i = 1, 2, 3$, corresponding to the three HSV components, thereby producing three distinct similarity values used in the retrieval process. Consequently, rotational alignment is performed before image indexing, and the following section details the implementation of angular rotation processing for specific motif images.

3.3. Image Rotation

Rotation refers to a circular movement of an object [55]. According to [56], varying rotation angles of the same object can result in significant differences in image feature

computation. Although the object remains identical, the matrix structure differs based on orientation. Therefore, a function capable of detecting the rotation angle is essential to identify the degree of angular transformation applied to the object.

Figure 6 illustrates changes in image orientation, highlighting the clearest rotational axis, which aligns with the original object's position. The image rotation process is implemented using the `rot90` function, covering angles from 0° to 315° .

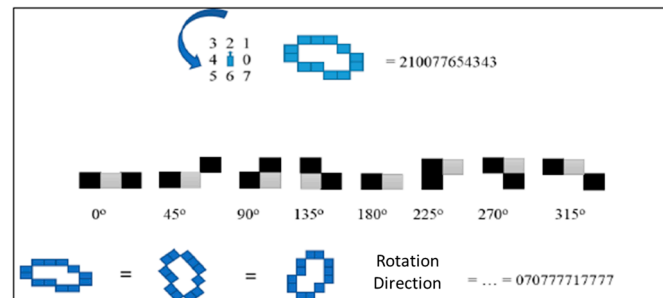


Figure 6. Details of the image rotation directions involving angles from 0° to 315° implemented in this study were redrawn. Source: [38]. The numbers that appear after the “=” sign represent the numeric encoding of the rotated motif shape. Each motif is traced along its boundary according to a predefined rotation direction (clockwise or counter-clockwise), and the sequence of boundary positions is then mapped into a string of numeric values. For example, the value 210077654343 corresponds to the ordered positions of the pixels that define the contour of the motif at a given orientation. Similarly, at the bottom of the figure, the sequence 070777717777 illustrates how the motif is represented as a rotation-invariant numeric pattern. This numeric encoding allows different rotations of the same motif ($0^\circ, 45^\circ, 90^\circ, \dots, 315^\circ$) to be consistently described and compared, ensuring that the retrieval system recognizes them as the same underlying motif regardless of orientation.

The detailed rotational directions applied in this study, ranging from 0° to 315° , are illustrated based on a redrawn diagram adapted from [56].

Figure 7 presents an example of a songket motif image rotated at angles between 15° and 180° to evaluate the retrieval system's ability to match rotated images. Some motifs exhibit identical axial alignment when rotated between 195° and 360° . Therefore, this study limits angular rotation edits to 12 intervals, covering angles from 15° to 180° .

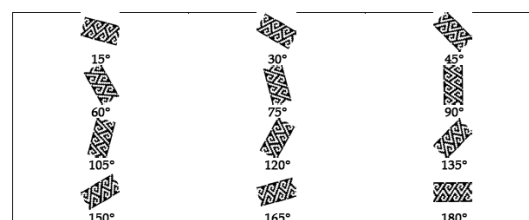


Figure 7. The songket motif images were subjected to editing processes for the purpose of facilitating image rotation matching.

The `rot90` function is used to detect 90° image array rotations. Specifically, $B = \text{rot90}(A)$ rotates matrix A by 90° counterclockwise. If A is an N -dimensional array, $\text{rot90}(A)$ performs the rotation in the plane defined by the first and second dimensions. The extended form, $\text{rot90}(A, K)$, applies a rotation of $K \times 90^\circ$ from position (1, 2) to the new orientation, with $K = (-2, 1)$ as illustrated in Figure 8.

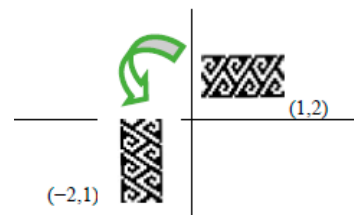


Figure 8. A 90° rotation of matrix A involves a counterclockwise direction. Source: [44].

Figure 9 illustrates the flow of Stage II, Part III, which outlines the image rotation and angle detection process. The procedure consists of the following nine steps:

1. Declaration of the rot90 function.
2. Identification of features from both the query and stored images.
3. The query image is flipped and matched against stored images to detect rotational differences through alignment.
4. A loop is executed based on the number of stored images.
5. If no rotational match is found, the process terminates.
6. If a match is found, a re-alignment process is initiated.
7. Matching the most similar points based on feature similarity or proximity.
8. Estimation of corresponding points to achieve accurate alignment.
9. Results are finalized and forwarded to the image indexing phase.

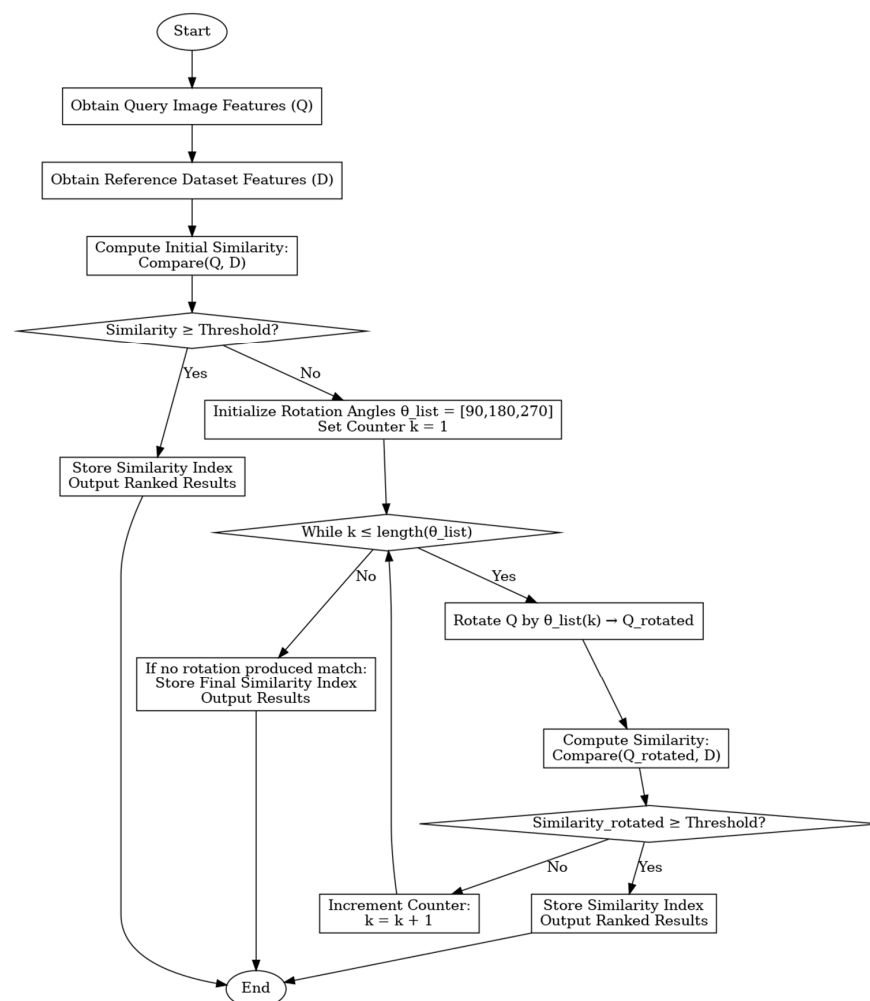


Figure 9. This algorithm compares the query image to the dataset with and without rotation to reliably retrieve similar images despite orientation differences.

The function $B = \text{rot90}(A, k)$ performs a counterclockwise rotation of matrix A by $k \times 90^\circ$. If only one input argument is provided, k defaults to 1. The function includes a safeguard to ensure that k is a scalar; otherwise, an error is raised (*rot90:kNonScalar*).

The rotation angle is determined using modular arithmetic: $k = \text{mod}(k, 4)$, limiting rotations to 0° , 90° , 180° , or 270° .

The conditional structure is as follows:

- If $k == 1$: Matrix A is flipped along dimension 2 and then permuted to switch the first and second dimensions.
- If $k == 2$: Matrix A is flipped twice, first along dimension 1 and then dimension 2.
- If $k == 3$: The matrix is first permuted and then flipped along dimension 2.
- If $k == 0$: No rotation is applied and A is returned unchanged.
- If k is not an integer, an error is raised.

Further logic accounts for conditional reshaping (*reshape*) and orientation adjustments based on the variable height. If $\text{height} > 0$, the matrix is rotated using *rot90* after reshaping. If not, the matrix is simply transposed.

These conditional checks ensure compatibility with multi-dimensional arrays and facilitate robust handling of image data with varying dimensions and orientations.

Image index classification is performed after identifying the dominant rotational feature vectors in the previous stage. Figure 10 illustrates the classification flow, where D_1 to D_n represent feature vectors used for mapping and matching. The symbols D_{n1-4} denote similar feature vectors ranked from highest to lowest based on percentage similarity.

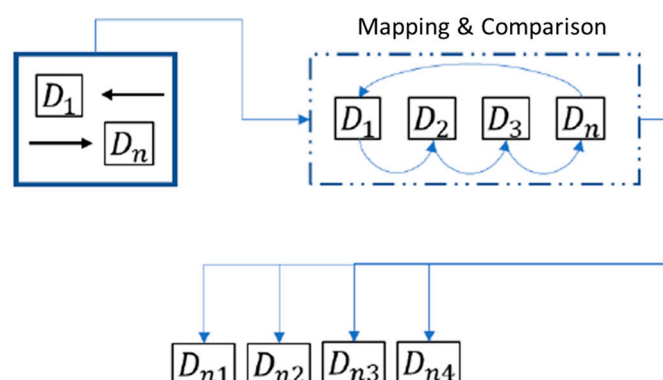


Figure 10. Classification flow. The symbols $D_1, D_2, \dots, D_n$ represent the **set of quadratic geometric distance values** calculated between the query image and each database entry. These values are then mapped and compared across all database images to generate secondary similarity measures, denoted as D_{n1}, D_{n2}, D_{n3} , and D_{n4} . In other words, the figure does not depict comparing two identical objects or testing the symmetry of one object under rotation, but rather the **systematic comparison of multiple distance values** from the query against every candidate image in the database. This mapping step ensures that similarity scores are consistently organized, allowing the framework to rank the database images according to their closeness to the query motif.

The sorted image index classification process and the procedure involve six key steps:

1. Extraction of feature vector similarity results.
2. Sorting of similarity values.
3. Re-plotting the sorted indices.
4. Ranking indices from highest to lowest similarity percentage.
5. Final classification output is generated.
6. The retrieval results are displayed on the songket motif image retrieval system interface.

Accordingly, the previous discussion on the complete workflow of the proposed system is summarized in Figure 11.

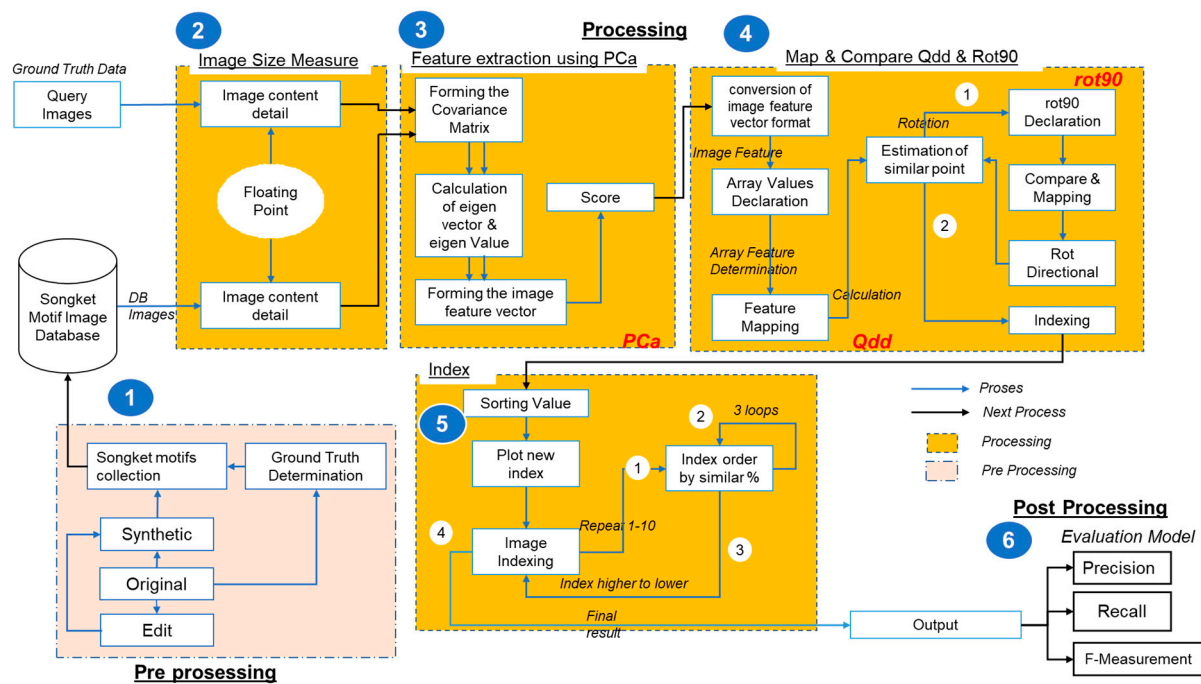


Figure 11. This framework depicts the proposed image retrieval model integrating Principal Component Analysis (PCA) and rotational invariance via *ROT90*. The process involves dataset preparation (synthetic and original motifs), image size normalization, PCA-based feature extraction, rotation mapping and similarity estimation, indexing of retrieved images, and evaluation using precision, recall, and F-measure to assess retrieval performance for rotated songket motif images.

The development and implementation of the songket motif image retrieval model demonstrated the effectiveness of combining Principal Component Analysis (PCA) with Quadratic Geometric Distance (QGD) techniques to address the long-standing issue of rotational variance in image retrieval tasks. This study specifically focused on the implementation phase of the model and emphasized robust preprocessing, precise feature extraction, and efficient image classification.

At the core of the system lies a carefully curated dataset consisting of 413 original songket motif images and 4956 synthetically rotated images. The inclusion of systematically rotated images enabled the model to simulate real-world variations and evaluate the retrieval algorithm's sensitivity to angular transformations. Metadata structuring in Stage I provided essential image properties (i.e., width, height, and bit depth), which were instrumental in ensuring consistency during the preprocessing and normalization stages.

The application of PCA in Stage II effectively reduced the dimensionality of high-resolution images while preserving essential structural features, particularly for motifs with intricate woven details [54]. The use of covariance matrices for eigenvalue computation allowed for the identification of dominant components within each motif, which were then used as inputs for similarity evaluation. This addressed the computational challenge highlighted by [51], enabling faster and more scalable analysis of large image sets.

The integration of the QGD technique allowed for a nuanced similarity comparison by evaluating geometric properties within *HSV-transformed* images. By computing D_1 , D_2 , and D_3 as similarity scores across different channels, the model produced refined retrieval rankings. The incorporation of transposed vectors ($s1'$, $s2'$, $s3'$) further ensured structural fidelity during comparisons and minimized the semantic loss common in traditional vector-based retrieval methods.

Rotational alignment, a significant factor in motif comparison, was addressed through the implementation of the *rot90* function and a multi-angle simulation framework. By

limiting the rotation spectrum to 12 distinct angles (15° to 180°), the system ensured adequate angular granularity while minimizing redundancy. This design choice was informed by observed axial similarities in motifs rotated beyond 195° .

Stage III focused on classifying retrieved images based on similarity indices derived from the QGD outputs. The ranking process, spanning value extraction, sorting, and index plotting, facilitated accurate classification of motif images according to their percentage of similarity. This not only supported the retrieval system's precision but also enhanced the user interface experience by presenting results in a ranked format, aligning with expectations in cultural heritage applications.

Overall, the retrieval model achieved its objective of accurately identifying songket motifs across rotational variations, addressing a key challenge in heritage digitization and pattern preservation. The model's modular structure further supports scalability and potential integration with larger national digital archives, such as those managed by the Department of National Heritage.

3.4. Definition of Technique

To ensure clarity and consistency, the techniques compared in this study are formally defined as follows:

1. PCA Technique

The Principal Component Analysis (PCA)-based retrieval approach is applied to reduce the dimensionality of image data by transforming pixel-level information into eigenvectors and eigenvalues. These compact feature vectors represent the most significant structural information of motifs, enabling efficient comparison across large datasets [5,6].

2. RPCA Technique

The Robust Principal Component Analysis technique is an enhanced variant of PCA, incorporating transformation and normalization processes to improve retrieval robustness. By aligning feature vectors through transformation functions, the method reduces sensitivity to scale and variance, thereby producing more stable similarity comparisons. This refinement is particularly effective when dealing with rotated or slightly distorted images [7].

3. QGD Technique

The QGD technique is based on Quadratic Geometric Distance (QGD), which measures similarity between images by evaluating geometric relationships across multiple feature channels. Unlike simple Euclidean distance, QGD accounts for quadratic forms and spatial relationships, allowing more accurate discrimination of motif shapes and textures [8].

4. PCAQGD Technique

The PCAQGD technique, developed in this study, integrates PCA-based feature extraction (PCA) with QGD similarity measurement (QGD). This hybrid model enhances retrieval accuracy by combining compact eigenvector-based representations with robust geometric similarity evaluation. However, at this stage, rotational invariance is not incorporated.

5. PCAQGD + Rotation Technique (Proposed Method)

The PCAQGD + Rotation technique represents the novel contribution of this research. It extends the PCAQGD model by introducing a rotation-invariance module. Images are systematically rotated (0 – 180°) and similarity is re-evaluated using QGD, ensuring that motif retrieval remains accurate despite orientation differences. This innovation directly addresses a key limitation in earlier CBIR systems applied to textile motifs, where rotation commonly degraded retrieval performance.

By clearly defining these techniques, the methodological foundation for this study is established. Each technique serves as a comparative benchmark, with the proposed PCAQGD + Rotation method positioned as the key innovation. This structured clarification ensures that subsequent experimental analyses can be interpreted with precision and consistency. The following section, therefore, presents the evaluation process and experimental results, where the performance of these techniques is systematically compared using benchmark motif datasets.

4. Testing and Evaluation

According to [57], information retrieval systems must undergo a testing and evaluation phase to assess performance and validate the developed model [58–62]. The choice of evaluation technique must align with the retrieval approach and the nature of the extracted features, whether text-based or image-based [61].

This chapter focuses on Phase IV, which evaluates the effectiveness of the proposed songket motif image retrieval model using 49 ground-truth query images selected by 15 general respondents and refined by expert reviewers during Phase II. The queries were tested against a dataset comprising 413 original and 4956 synthetically rotated songket motif images.

4.1. Testing

The testing and evaluation phase involved three expert respondents from the fields of cultural heritage and multimedia technology, who assessed the relevance of retrieval results from a user perspective.

Respondents were provided with minimal guidelines to allow independent judgment in selecting images they perceived as relevant. Phase IV testing involved 49 ground-truth query images evaluated against a test dataset of 413 original and 4956 synthetically rotated songket motif images. The system testing phase lasted 45 min, followed by 1 h and 15 min for relevance assessment. Both evaluations were conducted concurrently. Respondents marked relevant matches with a (✓) and irrelevant ones with an (×). Figure 12 lists the 49 ground-truth songket motif queries used, as identified in Phase II.

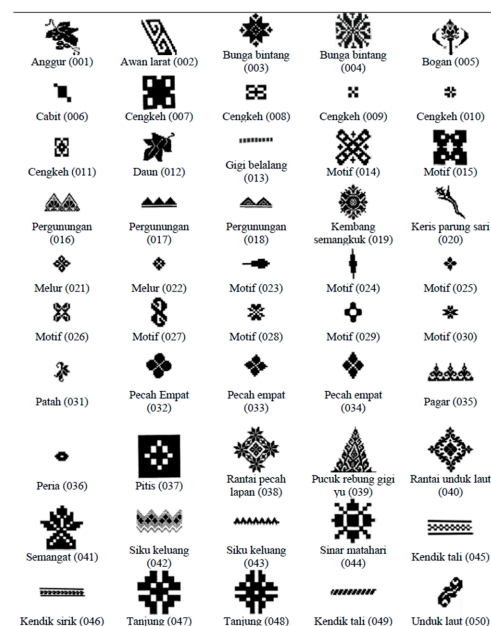


Figure 12. A total of fifty query images were employed by respondents to systematically evaluate the retrieval system's performance.

The results were used as training data to evaluate both the existing and proposed image retrieval systems. Figure 13 illustrates the post-processing evaluation workflow. The retrieved results were then validated by users to determine perceived relevance.

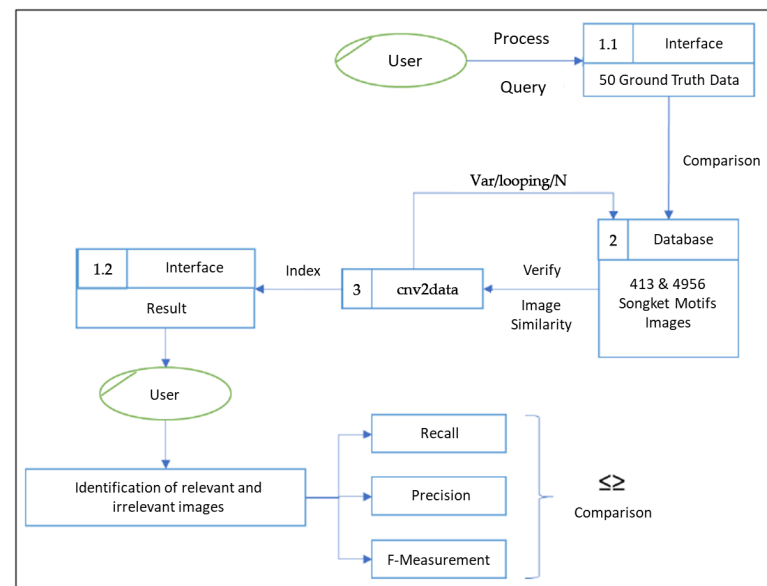


Figure 13. Flowchart illustrating the evaluation process at the post-processing stage.

4.2. Result

This section presents the evaluation and discussion of results obtained from testing the image retrieval system, which was conducted using 49 query images. The subsequent subsections provide detailed results of the comparative evaluation using precision, recall, and F-measure metrics.

4.2.1. Precision Evaluation

The precision calculation formula aims to determine the percentage accuracy of retrieved songket motif images from the database, focusing specifically on the retrieval precision. As previously defined in Chapter II, the precision technique is formulated as

$$\text{Precision} = \frac{\text{Number of relevant images successfully retrieved}}{\text{Total number of retrieved images}} \quad (7)$$

The PCA technique is a baseline content-based image retrieval (CBIR) approach that utilizes Principal Component Analysis (PCA) for feature extraction and dimensionality reduction. PCA transforms image data into eigenvectors and eigenvalues, producing compact feature representations that can be compared across a dataset. This method has been widely applied in image retrieval systems due to its ability to reduce computational complexity while preserving essential structural information of images [5,6].

The Robust Principal Component Analysis (RPCA) technique is an enhanced version of PCA, in which transformation functions and normalization steps are incorporated to improve retrieval robustness. In particular, RPCA addresses issues of variance and scale by aligning feature vectors before comparison, thereby achieving higher precision in retrieval tasks. Prior works in visual semantic embedding and rotation-invariant feature extraction support the need for such improvements in image retrieval [7].

The Quadratic Geometric Distance (QGD) is a similarity measure. Unlike traditional Euclidean or cosine distances, QGD evaluates geometric similarity across multiple feature channels, making it effective for distinguishing images with similar color and shape distri-

butions. This metric has been recognized in recent CBIR studies as more robust in handling variations in texture and structural features [8].

Building on these foundations, the present study introduces the PCAQGD technique, which integrates PCA-based feature extraction with QGD similarity measurement (QGD) into a single framework. Finally, the PCAQGD + Rotation technique is the proposed method, which extends this model by incorporating a rotational invariance module to address orientation differences in textile motifs, a limitation not sufficiently addressed in previous work.

The PCA technique achieved the highest precision result at 96%, involving query IDs 001–012 (67%, 100%, 75%, 100%, 67%, 100%, 100%, 100%, 100%, 100%, 100%, 100%), 015 (100%), 016 (100%), 018 (100%), and 020–050 (100%, 67%, 100%, 100%, 100%, 71%, 100%, 100%, 100%, 100%, 100%, 67%, 75%, 100%, 50%, 75%, 50%, 100%, 100%, 100%, 100%, 100%, 100%, 50%, 100%, 100%, 100%, 100%, 100%, 100%). Conversely, the remaining 8% higher values were obtained through evaluations using the RPCA technique, specifically for query IDs 013 (75%), 014 (74%), 017 (71%), and 019 (59%). This result occurred because the calculation of relevant images retrieved divided by the total number of images retrieved was balanced.

The evaluation results show that the PCA technique consistently produced the highest precision values, achieving up to 96% in several queries. In comparison, the RPCA technique obtained slightly higher precision for specific queries, while the QGD technique yielded the lowest precision values overall. The PCAQGD + Rotation technique demonstrated competitive results, though its precision percentage appeared lower due to a more imbalanced set of retrieved images.

Additionally, four query images achieved high precision values between 70% and 79%, specifically query IDs 027, 033, 034, and 039. A total of 14 query images fell within the moderate category, achieving precision values between 50% and 69%. Furthermore, 19 query images were categorized as low precision, and 11 as very low precision. This outcome was attributed to a relatively smaller number of relevant images available in the database for these query images compared to those achieving higher precision. This scenario highlights one strength of the QGD technique, which is its ability to effectively identify similarities in color features. The QGD technique is widely utilized in CBIR systems to detect similar color characteristics. Images closely resembling query images in color features result in shorter similarity distances. Conversely, images lacking color similarity yield longer similarity distances, leading to the retrieval of many images that are less relevant in terms of shape but identified as similar by the system to populate the retrieval result set.

Subsequently, the plotted data in the graph are arranged in ascending order from lowest to highest values. Figure 14 indicates that the PCA technique dominates the graph due to its consistently high precision values, reflecting a balanced retrieval outcome between relevant and total retrieved images.

However, calculating precision values alone is insufficient to fully demonstrate the performance evaluation of the techniques tested. Thus, the next evaluation involves calculating recall values for 49 query images related to songket motif images.

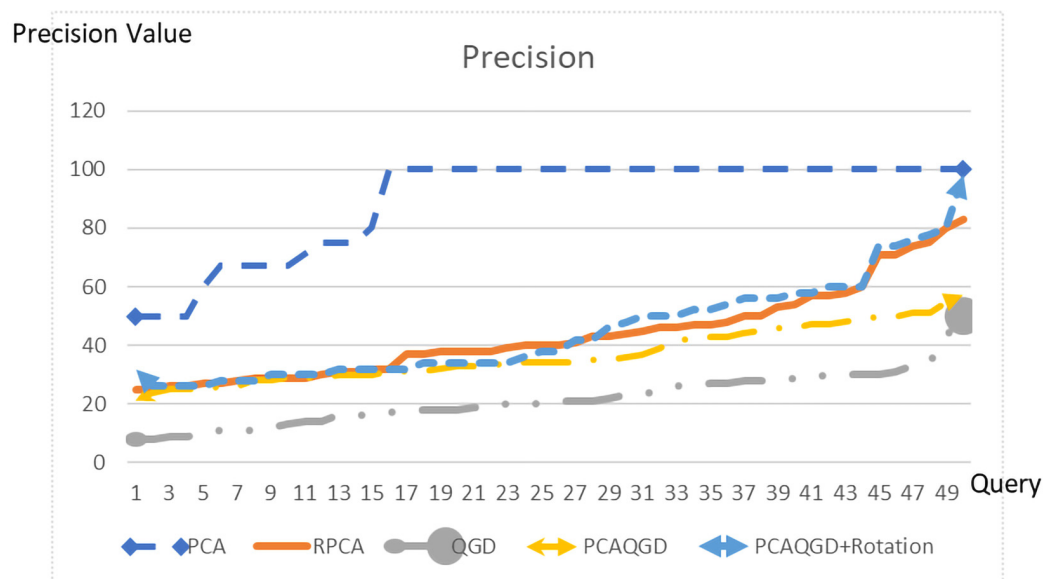


Figure 14. Plot a graph illustrating the precision values computed for 49 training image data of songket motifs across five image retrieval techniques.

4.2.2. Recall Evaluation

Both precision and recall techniques are essential and complementary metrics for evaluating the accuracy and relevance of retrieved images in relation to the query image and the stored dataset. These metrics are also critical for demonstrating the effectiveness of an image retrieval application. This section presents the assessment of recall percentage calculations. The recall metric is defined as follows Equation (8):

$$\text{Recall} = \frac{\text{Number of images successfully retrieved}}{\text{Total number of relevant images in the database}} \quad (8)$$

The recall value achieved by the PCAQGD + Rotation technique was 40%, which was notably higher than the recall performance of the other retrieval methods evaluated. In addition, a recall value of 46% was observed for both the PCAQGD and PCAQGD + Rotation techniques, indicating comparable effectiveness across these methods. This outcome corresponded to the following query IDs: 001, 009, 015, 021, 028, 029, 030, 032, 033, 035, 036, 037, 040–043, 045–048, and 049.

Moreover, the PCAQGD technique alone demonstrated superior recall performance, achieving a recall rate of 100% for query IDs 002, 005, 016, 023, and 034. In contrast, the RPCA technique yielded the highest recall percentages for only two queries—IDs 014 and 017—both of which recorded recall values of 4%.

Finally, three query IDs—018 (66%), 020 (100%), and 049 (100%)—exhibited identical recall percentages, highlighted in light brown, representing 6% of the comparative results.

With reference to the average recall percentages obtained, the results indicate that the PCAQGD + Rotation technique demonstrated the highest performance compared to the other methods, achieving an average recall of 97.24%. This outcome is attributed to the fact that the relevant retrieved images closely matched the total number of relevant images present in the database.

In contrast, the other techniques produced lower average recall values: PCA recorded 16%, RPCA achieved 86%, QGD yielded 40%, and PCAQGD reached 91.18%.

The plotted graph in Figure 15 was generated by arranging the recall values in ascending order, from the lowest to the highest. This approach was adopted to highlight the incremental differences in recall performance observed during the evaluation.

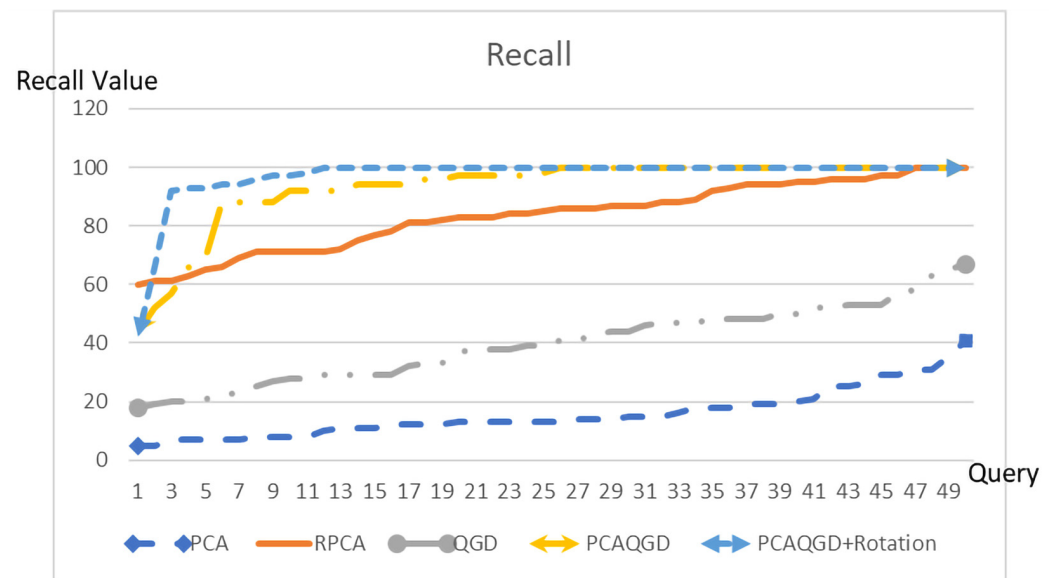


Figure 15. Plot a graph illustrating the recall values computed for 49 training image data of songket motifs across five image retrieval techniques.

Nevertheless, both precision and recall metrics should not be regarded as fully sufficient for comprehensively assessing the effectiveness of an image retrieval system. Therefore, the F-measure, or the harmonic mean of precision and recall, was employed to produce a single representative value. This approach enables more accurate comparisons and validation of retrieval performance [63].

4.2.3. F-Measurement

The F-measure (Equation (9)) reflects the harmonic mean of precision and recall, thereby providing a single balanced score that captures both the accuracy of retrieved images (precision) and the ability to return all relevant results (recall). Unlike precision or recall considered independently, the F-measure penalizes systems that perform well on one metric but poorly on the other. In the context of this study, a higher F-measure indicates that the retrieval method not only identifies relevant songket motif images accurately but also retrieves them consistently across multiple queries. Thus, the F-measure characterizes the overall robustness and reliability of each retrieval technique.

The formula for computing the F-measure is expressed as follows Equation (9):

$$F - measure = \frac{2 \times (Precision \times Recall)}{Precision + Recall} \quad (9)$$

Among all the techniques assessed, the PCA technique recorded the highest individual F-measure, with a single query—ID 029—achieving a score of 58%, representing 2% of the total cases evaluated.

In the case of the RPCA technique, 13 query IDs exhibited the highest F-measure values, accounting for 26% of the overall results. The corresponding query IDs and percentages were as follows: 002 (57%), 003 (52%), 005 (53%), 006 (58%), 008–011 (61%, 68%, 68%, 81%), 014 (73%), 016–018 (49%, 82%, 68%), and 035 (49%).

In contrast, the QGD technique did not yield any queries with top F-measure values.

For the PCAQGD technique, nine query IDs achieved the highest F-measure scores, representing 18% of the total observations. These were query IDs 023 (45%), 028 (61%), 030 (51%), 032 (51%), 037 (46%), 042 (47%), 043 (57%), 045 (52%), and 046 (50%).

Notably, the PCAQGD + Rotation technique produced the greatest number of top F-measure results, with 22 queries achieving the highest percentages, representing 44%

overall. The respective query IDs and scores were 007 (67%), 012 (88%), 013 (99%), 015 (68%), 019 (72%), 021 (74%), 022 (68%), 025–027 (72%, 51%, 86%), 031 (70%), 033 (88%), 034 (84%), 036 (72%), 038–041 (75%, 85%, 75%, 53%), 044 (51%), 047 (55%), and 048 (73%).

Additionally, three query IDs—001 (48%), 024 (41%), and 049 (59%)—recorded identical F-measure values across different techniques. In these instances, the PCAQGD and PCAQGD + Rotation methods demonstrated equivalent performance, collectively representing 6% of the comparative results.

In addition, to further distinguish the evaluation outcomes of the F-measure calculations, the overall mean values were computed to derive a single representative score for each technique assessed, including the technique developed in this study. The resulting mean F-measure values ranged from 26.04% to 59.72%.

According to the study conducted by [64], the acceptable average accuracy range for image retrieval systems is between 0.56 and 0.9. Accordingly, the results indicate that the PCAQGD + Rotation technique achieved a mean F-measure of 0.5972 (59.72%), placing it within this acceptable performance range and demonstrating that the proposed model functions effectively as a retrieval solution.

Furthermore, as presented in Figure 16, the F-measure evaluation of the technique developed in this study outperformed the four other methods assessed. Specifically, the PCAQGD + Rotation technique recorded an F-measure of 59.72%, representing an improvement of 4.3% compared to the RPCA technique, which achieved 55.42%. In contrast, the remaining techniques yielded lower mean F-measure values: PCA recorded 26.04%, QGD achieved 27.66%, and PCAQGD obtained 52.22%.

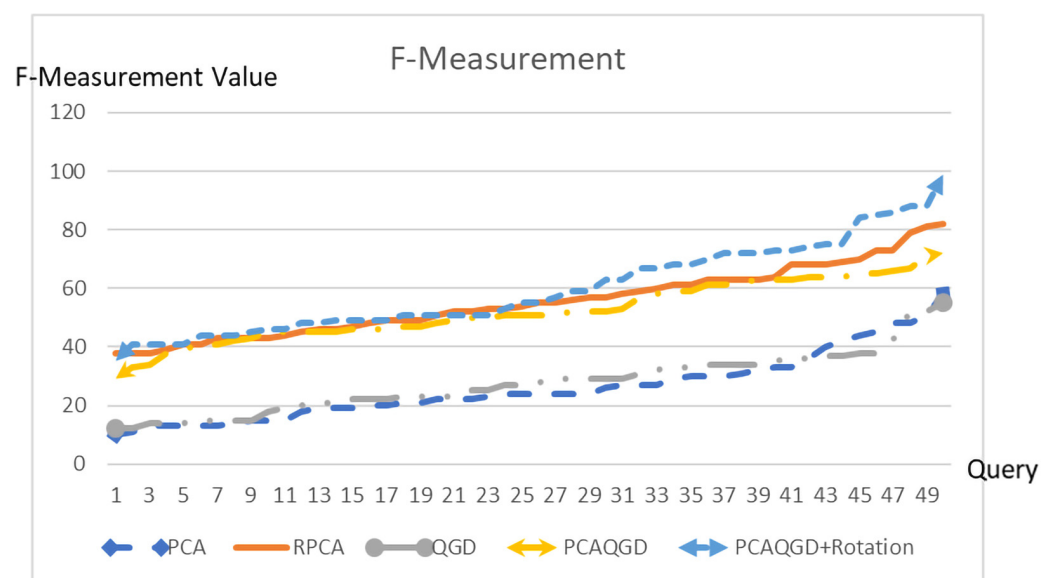


Figure 16. Plot a graph illustrating the F-measure values computed for 49 training image data of songket motifs across 5 image retrieval techniques.

The calculation of image retrieval performance using precision, recall, and the F-measure was described in the preceding subsections. The precision results demonstrated that the PCA technique consistently yielded the highest retrieval accuracy, whereas the QGD technique produced the lowest precision values.

Based on the conducted evaluation, most retrieval outcomes generated by the QGD technique alone were either less relevant or not relevant, resulting in a precision rate that declined to 22%.

Consequently, when combining the PCA and QGD techniques, the retrieval results showed a more balanced proportion of relevant and non-relevant images. However,

this combination still produced lower precision compared to the standalone PCA and RPCA techniques.

Nevertheless, the integration of the rotation function into the proposed technique led to improved retrieval outcomes, particularly for images edited with varying rotation angles during the recall assessment phase. This enhancement directly contributed to improved overall retrieval performance and increased the single-value F-measure evaluation for the PCAQGD + Rotation technique.

Accordingly, the F-measure evaluation of the PCAQGD + Rotation method reached 59.72%, representing a 4.3% improvement compared to the RPCA technique.

5. Conclusions

This study presented the development and evaluation of a novel Content-Based Image Retrieval (CBIR) model integrating Principal Component Analysis (PCA) and Quadratic Geometric Distance (QGD) techniques to address longstanding challenges in the retrieval of Malay songket motifs, particularly the issue of rotational invariance.

The model was rigorously tested on a curated dataset comprising 413 original and 4956 synthetically rotated songket motif images, demonstrating its ability to accurately retrieve motifs subjected to angular transformations. The inclusion of metadata-driven preprocessing, dimensionality reduction through PCA, and multi-angle similarity evaluation ensured that both the structural integrity and semantic meaning of the motifs were preserved throughout the retrieval process.

Quantitative evaluation using precision, recall, and F-measure metrics confirmed the effectiveness of the proposed approach. The PCAQGD + Rotation technique achieved a mean F-measure of 59.72%, surpassing the performance of all four comparative methods assessed in this study. This outcome validates the model's capacity to produce relevant and reliable retrieval results across a diverse range of motif orientations and complexities.

Beyond demonstrating technical efficacy, this research contributes meaningfully to the digital preservation of Malaysia's intangible cultural heritage. By bridging the gap between low-level image features and the high-level cultural semantics embedded in songket designs, the model supports more effective archiving, reference, and dissemination of traditional textile motifs. Such capabilities align with UNESCO's recognition of songket as a vital element of cultural heritage, underscoring the broader societal value of this work.

Future research should focus on expanding the dataset to include additional regional motifs and exploring the integration of deep learning frameworks to further enhance retrieval precision and scalability. Additionally, the development of user-friendly interfaces and interoperability with national digital heritage repositories will be critical to ensure the widespread adoption and long-term sustainability of this retrieval system.

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