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A Study on Image Processing and Deep Learning Methods for Wedding Photo Organization

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ABSTRACT

The rapid growth of digital wedding photography has resulted in extremely large image collections captured across multiple ceremonies. Manual organization of these photographs is time-consuming and often leads to inclusion of blurred, redundant, or improperly grouped images. This paper presents a structured framework for automated wedding photo organization using image preprocessing and Convolutional Neural Networks (CNNs). The proposed system performs resizing with padding, blur detection using the variance of Laplacian, duplicate removal using perceptual hashing, and event-based classification through a CNN model. The framework groups images into predefined wedding events such as Engagement, Mehndi, Haldi, Wedding, and Reception. The approach focuses on practical system design and mathematical modeling of the CNN architecture. The study demonstrates that integrating image processing with deep learning provides a scalable and efficient solution for event-wise photo managements.

Keyword : - convolutional neural network, image preprocessing, blur detection, duplicate removal, event classification.

1. INTRODUCTION

This modern wedding photography captures thousands of high-resolution images from various ceremonies held in quick succession. Organizing these images by hand takes a lot of effort and often results in inconsistencies during album preparation.

Traditional photo management systems depend on timestamps or manual tagging, which fall short for sorting events when multiple ceremonies happen around the same time. Recent advancements in deep learning, especially Convolutional Neural Networks (CNNs), offer strong abilities for classifying images. This work presents an automated framework that combines preprocessing methods with CNN-based classification. This approach aims to cut down on redundancy, remove low-quality images, and sort photographs by event. The main goal is to lessen manual work while enhancing consistency in wedding album preparation.

2. RELATED WORK

Image classification using deep learning has become a major area of study in computer vision. Convolutional Neural Networks (CNNs) have performed well in automatically extracting visual features like edges, textures, shapes, and object patterns. Tripathi [4] analyzed CNN-based image classification techniques and showed how effective they are at learning spatial features directly from images. Hassan et al. [14] reviewed deep learning methods, noting that CNNs are the best choice for image recognition since they can extract features automatically without manual input.

Many studies have aimed to improve image quality through preprocessing techniques. Blur detection is crucial for filtering out low-quality images. Francis and Sreenath [5] proposed methods for detecting blurred images using edge-based sharpness measures like the variance of Laplacian. This method checks image clarity based on intensity changes and is popular for its simplicity and effectiveness. Removing blurred images improves dataset quality and boosts classification performance.

Detecting duplicate and near-duplicate images is another key part of managing image datasets. Thyagharajan and Kalaiarasi [15] reviewed techniques for duplicate image detection in computer vision, including perceptual hashing and feature-based comparison methods. These techniques create compact representations of images, making it easier to identify visually similar ones. Perceptual hashing generates similar hash values for similar images, which is useful for large-scale duplicate detection.

Content-Based Image Retrieval (CBIR) techniques are also frequently used for analyzing image similarity. Hadid et al. [3] and Li et al. [7] provided thorough overviews of CBIR systems that rely on visual features like color, texture, and shape for image comparison. These features help find similar images based on content instead of metadata. The feature extraction techniques in CBIR systems enhance the accuracy of detecting image similarity and organizing datasets [8], [13].

Recent studies have looked into event recognition and image organization with deep learning. Glaser et al. [16] introduced transformer-based methods for event recognition in photo albums, highlighting the role of contextual information in classifying events. Similarly, Shivakumara et al. [1] developed a CNN-based system for classifying images from multicultural weddings, demonstrating that CNN models can effectively tell different wedding ceremonies apart based on visual traits like attire, decorations, and backgrounds.

Deep learning models have also been used in image clustering and dataset organization. Peng and Li [11] and Bouali et al. [18] showed that deep neural networks can learn useful feature representations that enhance image grouping and classification. These methods help organize large image collections more effectively.

While significant research has focused on image classification, blur detection, duplicate removal, and CBIR, most studies treat these techniques separately. There has been little work that combines preprocessing techniques with CNN-based event classification in a single framework aimed at wedding photo organization. Wedding photographs pose unique challenges because of differences in lighting, event settings, and visual appearances.

Therefore, this work suggests a unified framework that merges image preprocessing, blur detection, duplicate removal, and CNN-based classification to offer an efficient and practical solution for automating wedding photo organization

3. PROPOSED METHADOLOGY

This paper presents a practical framework for organizing wedding photographs automatically. It combines image processing techniques with deep learning-based classification. The main goal of this work is to create a system that helps photographers and families manage large collections of wedding photos easily. The proposed method aims to reduce manual work while ensuring that only high-quality and relevant images appear in the final organized output [1], [2].

The overall workflow of the proposed system is shown in Fig. 1. The system takes raw wedding images as input and processes them through a series of clear stages. These stages include image preprocessing, quality assessment, duplicate image removal, and event-based classification. Each stage addresses a specific problem commonly faced during wedding photo selection and album creation, such as variations in image quality, redundancy, and grouping by event [5], [15]. The final output consists of folders organized by event, making it easier for photographers and families to browse photos and prepare albums [16].

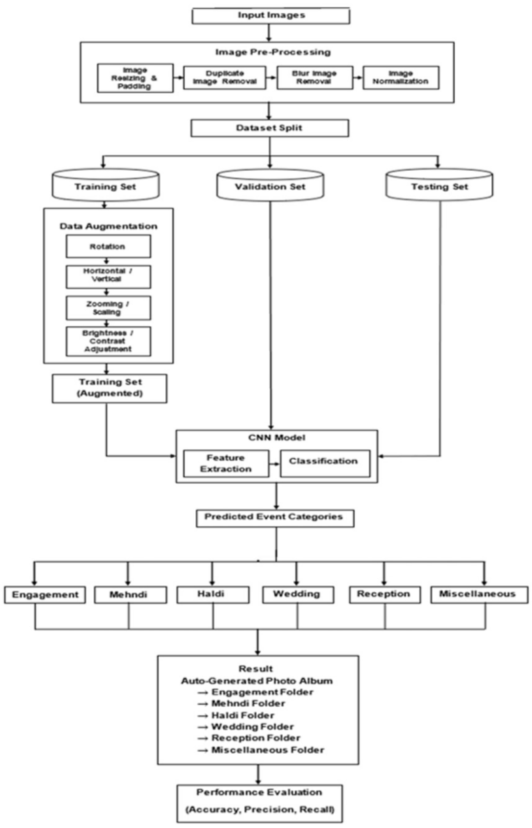

Fig -1: Block diagram illustrating the workflow of the proposed wedding photo organization system.

3.1 Image Preprocessing

All images are resized to a fixed dimension while keeping the aspect ratio using padding. We use pixel normalization to scale intensity values between 0 and 1: During training, we apply data augmentation, including rotation and horizontal flipping, to improve generalization.

Fig -2: Sample results of image preprocessing showing resizing with padding, normalization, and removal of duplicate and blurred images.

Fig -3: Data augmentation applied to training images

3.2 Image Blur Detection

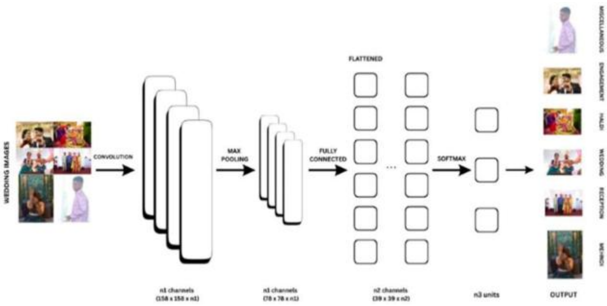

Fig -4: CNN architecture used for wedding event classification.

The CNN architecture for event classification is shown in Figure 5. It outlines the series of convolution, pooling, and fully connected layers [14], [17]. This design allows the model to learn visual features from wedding photographs and effectively tell different event categories apart. Using several convolution and pooling layers helps capture both low-level and high-level image features that are important for classifying wedding events.

Example: CNN mathematical model of real image from dataset

Step 1: Input Image from Dataset

A real Haldi ceremony image of size 293 × 439 pixels (RGB) is used as input to the CNN model. Each pixel contains Red, Green, and Blue intensity values.

Fig -5: Input Haldi ceremony image taken from the dataset

This image is used to demonstrate the mathematical working of the Convolutional Neural Network (CNN). Since the full pixel matrix is large, a small portion is extracted to demonstrate the CNN mathematical operations. The complete image is used during actual training and classification.

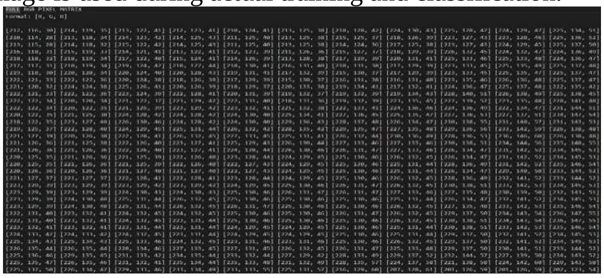

Fig -6: Screenshot of a partial pixel matrix of the input Haldi ceremony image

Step 2: Extraction of a Small Pixel Region for Demonstration

The original input image is very large (293 × 439 pixels). To clearly show how CNN works mathematically, a small 5 × 5 pixel area is taken from the original RGB pixel matrix.

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[212, 116, 30] [214, 119, 35] [213, 122, 41] [212, 123, 41] [210, 124, 41]
[210, 114, 28] [213, 118, 34] [214, 123, 42] [214, 125, 43] [211, 125, 40]
[213, 115, 28] [214, 118, 32] [215, 122, 42] [214, 125, 43] [211, 125, 40]
[216, 118, 31] [215, 119, 33] [214, 121, 41] [213, 122, 41] [212, 123, 39]
[218, 118, 32] [218, 119, 34] [217, 122, 40] [215, 124, 41] [214, 126, 39]
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Fig -7: Screenshot showing the exact 5 × 5 pixel region extracted from the original RGB image for demonstration

4. RESULTS AND ANALYSIS

The proposed framework improves the dataset by removing blurred and duplicate images. This leads to cleaner input for classification. Preprocessing makes the data more consistent and cuts down on redundancy.

The CNN model sorts images into event-based categories by learning visual features like attire, background, and stage decorations. Data augmentation strengthens the model's ability to handle changes in lighting and orientation.

The integrated workflow greatly lowers the manual work needed for album preparation. It also organizes wedding photographs in a structured way.

5. CONCLUSION

This paper introduced a structured framework for organizing wedding photos automatically using image processing and CNN-based classification. The system combines blur detection, duplicate removal, normalization, and event-based classification into one workflow.

The mathematical modeling of the CNN shows its ability to extract visual features for recognizing events. This approach provides a practical way to manage large wedding photo datasets and can be adapted for other event-based image management tasks.

Future work will focus on full implementation, evaluating performance, and comparing it with transfer learning models.

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