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Deep Learning-Based Image Classification of *B.1-KWK-Perseorangan* Forms Using K-Means and Convolutional Neural Networks

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Abstract

The verification process *of B.1-KWK-Perseorangan* forms at General Election Commission (KPU) is still conducted manually, resulting in time-consuming procedures and increasing the risk of document misclassification. The application of deep learning provides a promising solution for improving the efficiency and accuracy of administrative election document image classification. This study aims to analyse the capability of Convolutional Neural Networks (CNN) in classifying images of *B.1-KWK-Perseorangan* forms and to investigate the effect of K-Means as an initial image segmentation stage on improving classification accuracy and the effectiveness of document verification. The proposed method employs a deep learning approach by integrating K-Means for image segmentation and CNN for image classification. The research workflow consists of image preprocessing, segmentation, model training, and performance evaluation. The dataset comprises digital images of *B.1-KWK-Perseorangan* forms from the 2024 election, provided by the KPU of Sungai Penuh City, with an image resolution of 512 × 783 pixels. The experimental results demonstrate that the proposed model achieved an accuracy of 94% and a macro-average F1-score of 0.95, indicating that the integration of K-Means and CNN is effective for the classification of B.1-KWK-Perseorangan form images. Furthermore, the developed model has the potential to improve the speed, consistency, and accuracy of document verification within the KPU, while supporting the development of more effective, accurate, and efficient Deep Learning-based classification systems for election administrative documents.

Keywords: Deep Learning, CNN, K-Means, Image Classification, *B.1-KWK-Perseorangan* Forms.

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1. Introduction

The rapid advancement of Artificial Intelligence (AI) has become one of the primary drivers of digital transformation across various sectors, including government, by enabling systems to process data more efficiently, accurately, and consistently while reducing reliance on manual procedures [1], [2]. One of the most significant branches of AI is computer vision, which enables computers to automatically recognize, interpret, and analyse visual information from digital images [3]. This advancement has been further accelerated by the development of deep learning, particularly CNN, which are capable of automatically extracting discriminative visual features without requiring manual feature engineering. Consequently, CNNs have been widely adopted for a variety of image classification tasks [1], [4]. These technologies have been successfully applied in numerous domains, including handwritten text recognition, facial identification, medical image analysis, digital security systems, and image-based administrative document management [3]. The application of deep learning to image classification has demonstrated considerable potential in supporting the digitalization of public administration by enabling faster, more accurate, and more consistent document processing [2], [5]. Such capabilities have become increasingly important in election administration, where large volumes of documents must be verified within limited timeframes, creating a need for automated classification systems that improve efficiency while minimizing human error [6], [7]. To date, the verification of Model B.1-KWK-Perseorangan forms at the KPU has largely relied on manual inspection, resulting in lengthy verification processes and potential inconsistencies in determining administrative verification outcomes [6]. This form serves as an essential document required for independent candidate registration in regional elections, as stipulated in the General Election Commission Regulation Number 8 of 2024 [8]. Previous studies have demonstrated that CNNs achieve high performance in classifying various visual objects, including handwritten characters, plants, food products, batik patterns, and many other image categories[9], [10], [11]. Other studies have reported

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that K-Means clustering enhances image representation by performing segmentation prior to the classification stage [12], [13], [14]. However, studies specifically addressing the classification of election administrative document images, particularly B.1-KWK-Perseorangan forms, remain limited. Furthermore, the integration of K-Means as a preprocessing segmentation technique before CNN-based classification has received relatively little attention in research focusing on election-related documents [12], [15]. Motivated by these research gaps, this study proposes an integrated K-Means–CNN framework to enhance image feature quality and improve the effectiveness and accuracy of administrative document verification within the KPU [1].

This study adopts a quantitative experimental approach to evaluate the performance of a deep learning model in classifying images of *B.1-KWK-Perseorangan* forms into two categories: *Memenuhi Syarat* (MS) and *Tidak Memenuhi Syarat* (TMS). The research begins with the collection of digital image datasets obtained from the KPU of Sungai Penuh City, followed by a preprocessing stage consisting of image resizing, grayscale conversion, rescaling, and data augmentation to standardize image quality before segmentation and classification. These preprocessing procedures are essential because image quality directly affects the model's ability to learn meaningful visual representations. Therefore, representative input data are required to ensure optimal model training and improved classification performance [5], [16].

Following preprocessing, the images are segmented using the K-Means clustering algorithm, which groups pixels according to their visual similarity to produce a simpler and more structured image representation. The segmented images are subsequently used as inputs to a CNN architecture composed of convolutional layers, ReLU activation functions, Batch Normalization, MaxPooling, GlobalAveragePooling2D, and fully connected (Dense) layers, enabling the automatic learning of visual document features. Model performance is then assessed through training, validation, and testing phases to objectively evaluate classification capability based on predictions generated from unseen test data.

The use of K-Means in this study is motivated by previous research demonstrating its effectiveness in improving image segmentation by clustering pixels according to similar visual characteristics [12], [15]. Studies involving image classification of chili peppers, marine organisms, and tomato fruits have also shown that K-Means effectively separates object characteristics, resulting in more representative image features prior to classification [12], [13], [14]. This approach is particularly suitable for *B.1-KWK-Perseorangan* form images, which exhibit variations in document quality, pixel intensity, and lighting conditions. Consequently, an image segmentation stage is required to generate more informative inputs for the CNN model, thereby improving the overall classification performance.

The adoption of CNN in this study is also motivated by numerous previous studies that have demonstrated its capability to automatically extract discriminative visual features without requiring manual feature engineering [1], [4]. Extensive research on the classification of handwritten text, regional scripts, batik patterns, signatures, and plant images has consistently shown that CNN achieves high classification accuracy across a wide range of visual data types [17], [18], [19], [20], [21]. The primary distinction between this study and previous work lies in the application domain, namely election administrative documents, as well as the integration of K-Means as a segmentation stage prior to CNN-based classification. This integrated approach is expected to generate more representative image features, thereby improving the overall classification performance of the proposed model.

This study focuses on the development of an image classification model for *B.1-KWK-Perseorangan* forms by combining K-Means Clustering and CNN to achieve a faster, more accurate, and more consistent document verification process. The proposed approach is expected to contribute to the advancement of Deep Learning-based administrative document classification systems while providing an alternative solution to support the digitalization of administrative verification processes within the KPU of Sungai Penuh City.

2. Methods

This study adopts a quantitative approach with an experimental method to develop an image classification model for *B.1-KWK-Perseorangan* forms by integrating K-Means and Convolutional Neural Networks (CNNs). The research workflow is systematically organized, beginning with data collection, followed by image preprocessing, image segmentation, image classification, and model evaluation. The overall research framework is illustrated in Figure 1.

Figure 1 illustrates the overall research workflow, which begins with the collection of a dataset consisting of images of *B.1-KWK-Perseorangan* forms obtained from the KPU of Sungai Penuh City. The collected dataset then undergoes a preprocessing stage comprising image resizing, grayscale conversion, rescaling, and data augmentation. These preprocessing procedures are intended to standardize the image size, quality, and visual characteristics, thereby producing a more representative dataset suitable for subsequent processing.

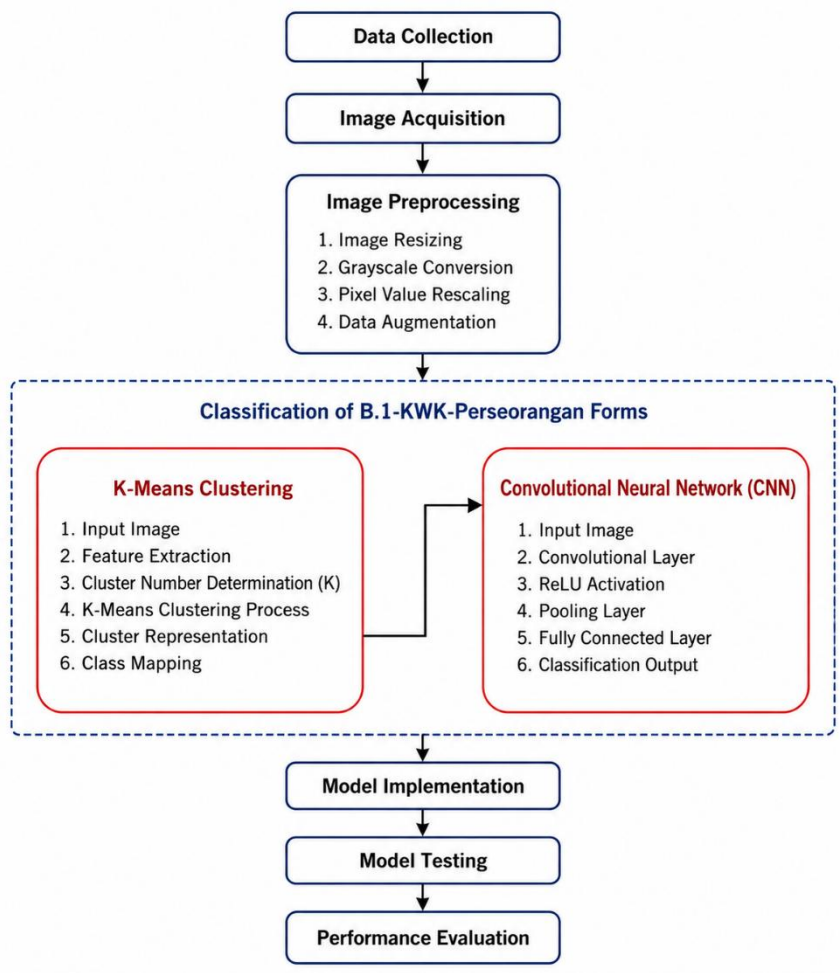


Figure 1 Research Framework

Following preprocessing, the images are segmented using the K-Means algorithm by grouping pixels based on the similarity of their visual characteristics. The segmented images are subsequently used as input to the CNN model, which classifies the images into two categories: *Memenuhi Syarat* (MS) and *Tidak Memenuhi Syarat* (TMS). Finally, the proposed model is evaluated using a testing dataset to assess its classification performance and to determine the effectiveness of integrating K-Means and CNN for the classification of *B.1-KWK-Perseorangan* forms.

2.1 Deep Learning

Deep Learning is a subfield of Machine Learning that employs multilayer artificial neural networks to learn complex patterns from data. This approach is capable of automatically learning hierarchical feature representations, making it widely applicable to image recognition, speech recognition, and natural language processing tasks [16]. In this study, Deep Learning serves as the primary approach for classifying images of *B.1-KWK-Perseorangan* forms, as it effectively captures the visual characteristics of the documents without requiring manual feature extraction.

2.2 K-Means

K-Means Clustering is an unsupervised learning algorithm that partitions data into clusters based on the similarity of their characteristics. In this study, K-Means is employed as an image segmentation technique by grouping pixels with similar visual characteristics, thereby producing a simplified image representation prior to the classification process using a CNN.

The centroid of each cluster is calculated using the following equation [22]:

$$V = \frac{\Sigma \frac{n}{i=1} xi}{n} \; ; \; i = 1,2,3, \ldots \ldots n \qquad (1)$$

where V denotes the centroid of a cluster, xi represents the i-th data point, and n is the total number of data points assigned to the cluster. The distance between each data point and its corresponding centroid is then computed using the Euclidean Distance metric:

$$d(x,y) = ||x - y|| = \sqrt{\Sigma}(xi - yi)2ni = 1 \; ; i = 1,2,3, \ldots . , n \qquad (2)$$

where xi and yi denote the i-th elements of data points x and y, respectively, and n represents the total number

of features. Through this iterative process, each pixel is assigned to the cluster with the nearest centroid until the centroid positions converge and become stable. The resulting segmented images are subsequently used as inputs for the image classification stage.

2.3. CNN

CNN are a deep learning architecture specifically designed for image processing through automatic feature extraction using convolutional layers. CNN are capable of learning various visual characteristics, including shapes, edges, textures, and patterns, making them widely adopted for a broad range of image classification tasks [23], [24]. In this study, a CNN is employed to classify images of *B.1-KWK-Perseorangan* forms into two categories: *Memenuhi Syarat* (MS) and *Tidak Memenuhi Syarat* (TMS).

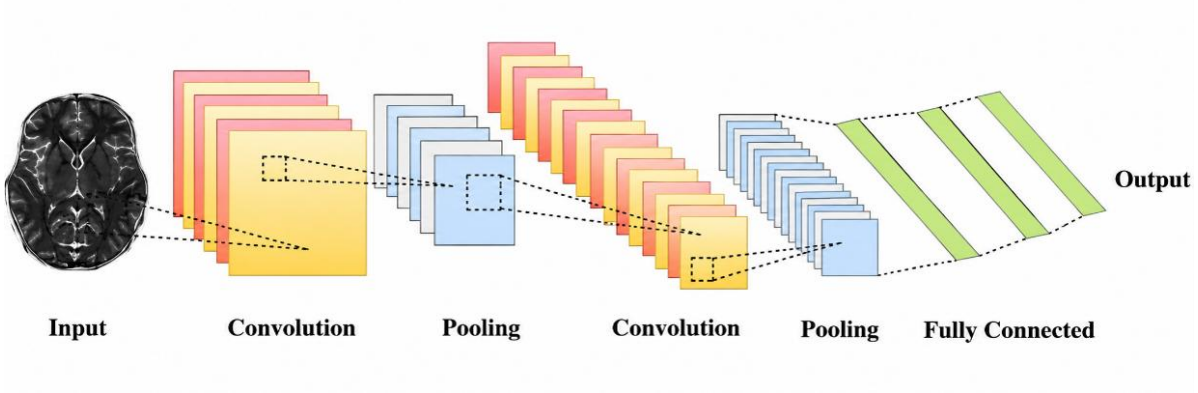


Figure 2 CNN Model Architecture

The proposed CNN architecture consists of two main components: the Feature Learning stage and the Classification Layer, as illustrated in Figure 2. The Feature Learning stage is responsible for automatically extracting discriminative features from the input images through convolutional and pooling layers. The extracted features are then passed to the Classification Layer, which performs the final classification and generates the predicted class label for each image.

3. Results and Discussions

This section presents the results of the proposed approach, which integrates K-Means Clustering with a CNN for the classification of *B.1-KWK-Perseorangan* form images. The discussion covers the dataset used in this study, the preprocessing procedures, the image segmentation process using K-Means, the training of the CNN model, and the evaluation of model performance based on the experimental results. Each stage is described systematically to assess the effectiveness of the proposed method in supporting the classification of administrative documents within the KPU.

3.1 Dataset

The dataset used in this study consists of digital images of Model B.1-KWK-Perseorangan forms from the 2024 Regional Election, obtained directly from the KPU of Sungai Penuh City. All images are stored in .jpg format and are categorized into two classes: *Memenuhi Syarat* (MS) and *Tidak Memenuhi Syarat* (TMS). A total of 1,000 images were used in this study and were divided into training, validation, and testing sets to facilitate model training and performance evaluation.

Table 1 Reserch Dataset

No.	Dataset	Number of Images	Format
1	*B.1-KWK-Perseorangan* Forms – *Memenuhi Syarat* (MS)	500	Jpg
2	*B.1-KWK-Perseorangan* Forms – *Tidak Memenuhi Syarat* (TMS)	500	Jpg
	Total	1000	-

As shown in Table 1, the dataset distribution reflects the allocation of images across the training, validation, and testing stages, ensuring an appropriate data partition for model development and evaluation.

3.2 Preprocessing

The preprocessing stage was performed to improve image quality prior to segmentation and classification. This stage includes image resizing, grayscale conversion, rescaling, and data augmentation. These procedures standardize the image dimensions, normalize pixel intensity values, and increase the diversity of the training data while preserving the original characteristics of the documents. Consequently, the preprocessing stage produces more representative images, thereby enhancing the effectiveness of the model learning process.



Figure 3 Preprocessing Results of *B.1-KWK-Perseorangan* Forms

As illustrated in Figure 3, the preprocessing stage produces images with more consistent quality and dimensions, making them suitable for the subsequent image segmentation stage using K-Means Clustering..

3.3 Image Segmentation Using K-Means

Image segmentation was performed using the K-Means Clustering algorithm by grouping pixels according to the similarity of their visual characteristics. The primary objective of this stage is to simplify the image representation, enabling important document features to be more clearly distinguished before the classification process using a CNN.



Figure 4 Image Segmentation of *B.1-KWK-Perseorangan* Forms Using K-Means

As shown in Figure 4, the K-Means algorithm successfully generates a more structured image representation. The segmented images are subsequently used as inputs to the CNN model, enabling it to learn the visual characteristics of the documents more effectively.

3.4 CNN Model Training

The CNN model was developed using the segmented images produced by K-Means as the primary input. Model training was performed using the training set, while the validation set was employed to monitor model performance at each training epoch and to identify the model with the best generalization capability.

As presented in Figure 5, both the training loss and validation loss exhibit a consistent downward trend throughout the training process. Conversely, the training accuracy and validation accuracy increase steadily, indicating that the model successfully learns the visual characteristics of *B.1-KWK-Perseorangan* forms and achieves stable convergence.

3.5 Final Model Evaluation

The final evaluation was conducted using the testing set, which was completely excluded from both the training and validation stages. Model performance was assessed using several evaluation metrics, including Accuracy, Precision, Recall, F1-score, and the Classification Report, to comprehensively evaluate the model's capability in classifying images of *B.1-KWK-Perseorangan* forms.

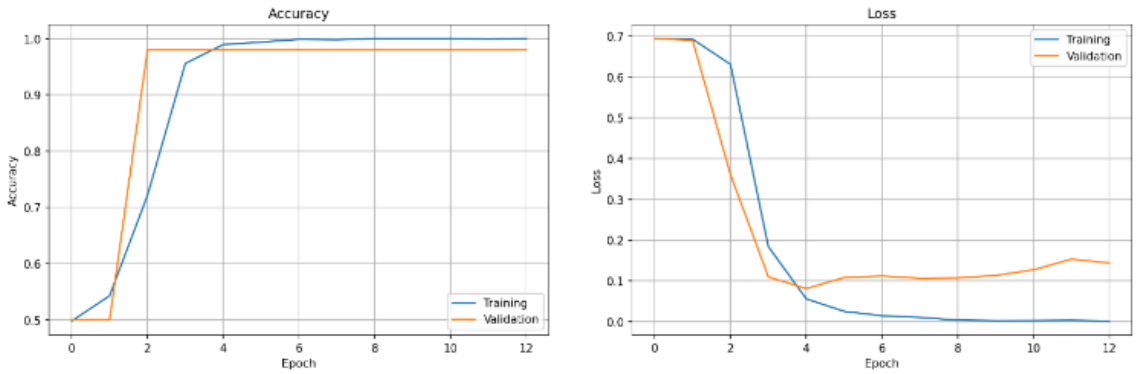


Figure 5 Training Loss, Validation Loss, Training Accuracy, and Validation Accuracy of the CNN Model

Table 2 Classification Report

Class	Precision	Recall	F1-Score	Support
Memenuhi Syarat (MS)	1.00	0.89	0.94	27
Tidak Memenuhi Syarat (TMS)	0.90	1.00	0.95	27
Accuracy	-	-	0.94	54
Macro Average	0.95	0.94	0.95	54
Weighted Average	0.95	0.94	0.94	54

As summarized in Table 2, the proposed model demonstrates satisfactory classification performance for both document categories. The obtained Precision, Recall, and F1-score indicate that the integration of K-Means Clustering and CNN effectively classifies *B.1-KWK-Perseorangan* form images while maintaining consistent predictive performance on the testing dataset.

4. Conclusions

This study successfully implemented an integrated K-Means Clustering and Convolutional Neural Network (CNN) framework for classifying images of *B.1-KWK-Perseorangan* forms at the KPU of Sungai Penuh City. The preprocessing and K-Means segmentation stages improved the quality of the image representations, enabling the CNN model to learn the visual characteristics of the documents more effectively.

The evaluation results indicate that the proposed model achieved an accuracy of 94%, with precision values of 1.00 for the *Memenuhi Syarat* (MS) category and 0.90 for the Tidak *Memenuhi Syarat* (TMS) category. The model also attained recall values of 0.89 for the MS category and 1.00 for the TMS category, while the corresponding F1-scores were 0.94 and 0.95, respectively. Furthermore, the macro-average precision, recall, and F1-score were 0.95, 0.94, and 0.94, respectively, whereas the weighted-average precision, recall, and F1-score were 0.95, 0.94, and 0.94. These results demonstrate that the proposed model provides robust and consistent classification performance across both document categories.

Overall, the findings suggest that the integration of K-Means Clustering and CNN has the potential to support the document verification process within the KPU by improving its speed, accuracy, and consistency. Future research is recommended to utilize larger and more diverse datasets and to investigate more advanced deep learning architectures or alternative image segmentation techniques in order to enhance the model's generalization capability and classification performance under a wider range of document image conditions.

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