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DETECTION OF DIRTY BOWEL DISEASE THROUGH PALM IMAGE ANALYSIS USING CNN-VGG16 ALGORITHM

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ABSTRACT

Early detection of disease is very important in improving the quality of human health. The quality of life of patients suffering from gross bowel disease can be significantly affected, including daily activities, work, and interpersonal relationships. One promising innovative method in the healthcare field is disease detection through palm image analysis. The solution to this problem is done by implementing the Convolutional Neural Network (CNN) algorithm using the VGG16 architecture model which can be operated by uploading palm images to detect Dirty Bowel Disease, Other Diseases (Not Dirty Bowel), and Healthy Hands through a web-based application. Based on the test results, the test accuracy value is 0.4800, F1-Score for the dirty gut disease category is 0.62, F1-Score for Other Diseases (Not Dirty Intestines) is 0.54, F1-Score for the Healthy Hands category is 0.29, and the overall F1-Score is 0.50. The white box test results show that the system can run well in all test scenarios applied. While the black box testing results show that the application functions as expected. In addition, the prediction results using the image import feature are supported by a confidence score with an average value of 48.89% for all three categories.

Keyword: Dirty Bowel Disease, Disease Detection, Deep Learning, Convolutional Neural Network (CNN), VGG16.

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1. INTRODUCTION

Early disease detection plays a crucial role in improving human health outcomes. According to [1], early diagnosis significantly enhances patient prognosis and enables timely interventions, ultimately reducing mortality rates and improving quality of life. Their study found that screening programs for diseases such as breast and colorectal cancer increased participation rates by 25% compared to the previous year. Furthermore, mortality rates among individuals who participated in early detection programs declined by up to 15% for breast cancer cases. These findings highlight the importance of early diagnosis in facilitating prompt treatment before a disease progresses to a more severe stage. In addition, about 70% of patients diagnosed in the early stages reported better physical and mental well-being compared to those diagnosed in later stages. Similarly, [2] emphasized that early detection allows for more effective interventions and appropriate treatment before a condition worsens. Faster diagnosis can also help lower overall healthcare costs, making time and financial efficiency key benefits. This is especially relevant today, as healthcare costs continue to rise and many patients lack access to adequate medical services [3]. Scalable early detection systems enhance healthcare accessibility for diverse populations and can be applied in various healthcare settings, from small clinics to large hospitals [4]. Proactive health monitoring not only supports disease prevention [5] but also helps alleviate the burden on healthcare providers and systems. In this context, advancements in artificial intelligence (AI) and image analysis technology have the potential to improve the accuracy and efficiency of early disease detection [6].

The quality of life for individuals suffering from dirty bowel disease can be significantly affected, influencing their daily activities, work performance, and interpersonal relationships. This condition often presents with severe symptoms such as abdominal pain, diarrhea, and fatigue, which severely disrupt patients' overall well-being [7]. Research by [8] has also shown that psychological stress can worsen the symptoms, underscoring the importance of stress management as part of the treatment strategy. The World Health Organization [9] reports a continuous increase in dirty bowel disease cases, with many people remaining undiagnosed or not receiving appropriate care. These figures emphasize the need for faster, more reliable diagnostic approaches to ensure patients can access timely and effective treatment [10]. Moreover, this disease has significant social and economic consequences, including reduced productivity and rising healthcare expenses [11]. [12] also emphasized the importance of patient education regarding disease management and lifestyle modifications, as these efforts can improve symptom control and treatment adherence. Thus, improving early detection and disease management is essential to enhance patient well-being and reduce the wider social impact. One promising innovation in the healthcare sector involves detecting diseases through palm image analysis. This method can serve as an early diagnostic tool by identifying health issues before clinical symptoms become apparent [13]. Certain patterns on the human palm are believed to reflect underlying health conditions, making palm image analysis a potential non-invasive diagnostic aid [2]. Recent studies have linked palm patterns to various health concerns, including metabolic disorders and infectious diseases [14]. With advancements in image processing and machine learning algorithms, palm image analysis could offer a useful means of detecting multiple diseases, including dirty bowel disease [10]. Furthermore, this approach can be integrated into telemedicine systems, allowing patients to undergo health evaluations remotely — a capability that has become increasingly important in the post-pandemic era [7].

For image recognition and processing tasks, the Convolutional Neural Network (CNN) algorithm has proven to be one of the most effective techniques. Designed to mimic how the human brain identifies patterns, CNNs are capable of efficiently recognizing critical image features [15]. They have been widely applied in various fields such as disease detection, facial recognition, and object classification. Thanks to their multilayer architecture consisting of convolutional and pooling layers, CNNs can process large, complex datasets and extract meaningful features [16]. This flexibility makes CNNs particularly valuable in artificial intelligence applications [17]. In fact, CNNs have outperformed traditional image recognition methods in many tasks, achieving high levels of accuracy [18]. [19] also demonstrated CNN's success in medical diagnosis, such as detecting cancer and heart disease, with impressive accuracy rates. Given these advantages, CNN is an excellent choice for developing disease detection systems, as it can learn from new data and continuously improve its predictive capabilities. Among CNN architectures, VGG-16 remains one of the most popular and widely used models in image processing applications. According to [20], VGG-16 achieved top rankings in the ImageNet Large Scale Visual Recognition Challenge

(ILSVRC). Known for its depth and complexity, the model consists of 16 trainable layers, enabling it to capture highly detailed image features [21]. Its strength lies in its ability to produce powerful feature representations, making it well-suited for various image classification tasks [20]. The use of uniform convolutional filter sizes in its architecture simplifies implementation while delivering excellent results, even when applied to smaller datasets [22]. Furthermore, VGG-16 has consistently performed well in image recognition competitions, demonstrating superior performance compared to other models [16]. As a result, it has become a preferred choice for both research and practical applications in image analysis.

Despite the availability of various disease detection methods, there remains a gap in research, particularly concerning dirty bowel disease. This condition is frequently undetected in its early stages, necessitating more sensitive and specific diagnostic techniques [10]. While preliminary evidence suggests that palm images could serve as a useful diagnostic tool, further research is required to fully explore this technique's potential [23]. Additionally, implementing CNN-VGG16 algorithms in this context could enhance detection accuracy and efficiency; however, challenges persist, especially in collecting sufficient and representative image data to train reliable models [14]. To date, no studies have specifically focused on utilizing palm images for disease detection, revealing a clear research gap. Therefore, further investigation is needed to evaluate the full benefits of this method, particularly for early detection of dirty bowel disease. The primary objective of this study is to develop and evaluate an innovative approach to detect dirty bowel disease using palm image analysis. It is expected that combining CNN-VGG16 algorithms with the distinctive features of palm images will improve diagnostic accuracy for this condition. Ultimately, to enhance public health outcomes, it is essential to establish a comprehensive methodology that integrates advanced detection technologies with existing medical knowledge. Based on this background, this study proposes implementing a web-based detection system for dirty bowel disease using the Convolutional Neural Network (CNN) algorithm with the VGG-16 model architecture. The dataset consists of images of healthy palms, palms affected by dirty bowel disease, and palms with other diseases (not dirty bowel disease).

Numerous studies have confirmed the effectiveness of deep learning, particularly CNN, in image classification tasks. [24] and [25] successfully applied CNN-VGG16 for peanut and eggplant disease classification, achieving accuracies of 96.7% and 99.4%, respectively. In medical imaging, [26] and [27] demonstrated high accuracy using deep learning for brain MRI classification and dilated convolution methods. Other applications include [28] achieving 98.96% accuracy in breast cancer detection through transfer learning, and [29] proposing channel pruning for CNN model optimization. In agriculture and infrastructure, deep learning has been effectively used for plant disease detection [30] and crack detection in concrete [31]. Advances such as Attention-Guided CNN models have also enhanced diagnostic accuracy for glaucoma (95.3%). Furthermore, research into gut microbiota highlights its crucial role in disease development, with [32] linking microbial imbalances to liver cancer progression. Studies by [33], [34], [35], and [36] emphasize evidence-based management and the impact of gut dysbiosis on non-communicable diseases, including IBS, obesity, and cancer.

2. METHODS

This study aims to detect dirty bowel disease through palm image analysis using the CNN-VGG16 algorithm. The research methodology adopts a combination of the Knowledge Discovery in Databases (KDD) framework and the Rapid Application Development (RAD) approach. According to [37], KDD is defined as a systematic process involving the selection, cleaning, transformation, and processing of data to identify meaningful patterns within large datasets. Similarly, [38], in their book Data Mining: Concepts and Techniques, describe KDD as a comprehensive process that encompasses data collection, preprocessing, and knowledge extraction. Meanwhile, as stated by [39], RAD emphasizes rapid application development through continuous prototyping and user feedback, enabling developers to respond swiftly to evolving user needs. [40] also highlights RAD's focus on close collaboration between developers and users, allowing teams to detect and address problems early in the development cycle.

In this study, the Knowledge Discovery in Databases (KDD) methodology was applied through five systematic stages. The Selection stage involved manually collecting 533 RGB palm images from Rumah Herbal Toga Citra Pondok Rosan patients and peers, with diagnoses confirmed by herbal therapy practitioners. These images were categorized into three classes: dirty bowel disease, other diseases, and healthy palms. In the Pre-processing stage, images were normalized by scaling pixel values to [0, 1], resized to 224×224 pixels, and augmented through rotation, translation, zooming, cropping, and flipping to improve data variation using TensorFlow's ImageDataGenerator, while testing data was only normalized. K-Fold Cross Validation was implemented for reliable model evaluation. The Transformation phase included feature extraction using a pre-trained VGG16 model (with fully connected layers removed), followed by Flatten and dense layers for three-class classification. The dataset was split using both train/test and train/validation/test schemes, ensuring balanced class distributions. New images were also preprocessed using OpenCV techniques before final predictions.

The Data Mining stage involved training two models: a CNN with three convolutional blocks and a VGG16 model with retained convolutional layers and a custom dense classifier. Both models used the Adam optimizer (learning rates: 0.001 for CNN, 0.00005 for VGG16), categorical crossentropy loss, and accuracy as the evaluation metric. Training was conducted over 30–80 epochs with batch sizes of 8, 16, and 32, applying consistent data augmentation strategies to improve image variation. Performance was assessed through accuracy, F1-score, classification reports, and confusion matrices. In the final Interpretation and Evaluation stage, the models were tested on unseen data, with accuracy and loss curves analyzed to monitor learning progress and overfitting risks. Confusion matrices and classification reports, generated from class probability outputs using np.argmax, provided detailed insights into precision, recall, and F1-score values, offering a comprehensive evaluation of each model's reliability in classifying palm images for dirty bowel disease detection.

In addition to applying the KDD methodology, this study also implemented the Rapid Application Development (RAD) approach, which comprises three main phases: Requirement Planning, Design, and Implementation. In the Requirement Planning phase, the researcher analyzed system needs for a web-based dirty bowel disease detection application, including user, hardware, and software requirements. The system targeted the general public concerned with digestive health, providing features such as image upload for palm-based detection, disease information, symptom descriptions, prevention suggestions, and healthy palm assessments. Hardware requirements included an Intel Core i3 processor, 4GB RAM, and standard input devices, while the software environment utilized Windows 11, Google Chrome for testing, and Draw.io for diagram development. The Design phase involved creating system architecture diagrams, including Use Case Diagrams to define actor interactions, Activity Diagrams for workflow descriptions, Sequence and State Diagrams to visualize process flows and state transitions, and Class Diagrams for system structure representation. Additionally, web interface mock-ups were prepared for the homepage, detection feature, disease information, and healthy palm information displays.

In the Implementation phase, system development began by constructing page layouts, an image upload feature for disease detection, and informational pages about dirty bowel disease, other conditions, and healthy palms. System testing was conducted using black box, white box (basis path technique), and accuracy testing for the image detection function. The system was built using the Flask framework to handle request routing and prediction processing, while image handling was managed through the Python Imaging Library (PIL). CNN and VGG16 models, trained separately on Google Colab with TensorFlow/Keras and ImageDataGenerator for augmentation, were evaluated using K-Fold Cross Validation, accuracy, F1-score, confusion matrices, and classification reports. The trained models in .keras format were then integrated into the Flask-based application, organized into templates/, static/, and model/ directories. RESTful APIs enabled seamless frontend-backend communication, with route configurations for the homepage, disease info, system info, image upload, and result display. Final prediction results provided class labels and confidence scores, offering a functional, interactive, and accessible web-based detection system.

3. RESULTS AND DISCUSSION

The modeling process for detecting dirty bowel disease was conducted using the Convolutional Neural Network (CNN) algorithm and the VGG16 architecture, following the stages of the Knowledge Discovery in Database (KDD) methodology. The process commenced with the Selection stage, during which palm images were collected from herbal therapists at the Toga Citra Herbal Clinic and classified into three distinct categories. In the Pre-processing stage, the images underwent normalization and various augmentation techniques, including resizing to 224×224 pixels, horizontal flipping, 20% zoom, random rotations up to 20 degrees, and contrast enhancement to improve data variability. The Transformation stage involved feature extraction, dimensionality reduction, splitting the dataset into training and testing subsets, normalizing feature values, and compiling the models. The Data Mining stage served as the core modeling phase, where both CNN and VGG16 architectures were trained using supervised learning approaches; the CNN model was optimized using the Adam optimizer with a categorical crossentropy loss function, while the VGG16 model utilized pretrained weights from ImageNet for transfer learning. The researcher conducted several training experiments by applying different data splitting schemes, beginning with an 80:20 split for training and testing data while employing varied data augmentation configurations for the training set in each trial.

Subsequently, a 60:25:15 split was tested for training, validation, and testing sets, also incorporating different augmentation strategies in each experiment. Another approach involved a 70:15:15 split with similar variations in data augmentation applied to the training data across multiple trials. Among these experiments, the most optimal model performance was achieved using the 60:25:15 data split configuration, as presented in detail in Table 1 below.

Table 1. Results of Model Training Using a 60:25:15 Dataset Split Ratio

No	Data	Epoch	Batch size	Optimizer	Model	F1-Score/Class			Test Accuracy	Final F1-Score
						1	2	3		
1	360 + aug train	50	16	Adam	CNN	0.51	0.20	0.00	0.5111	0.36
	3x/gambar k-fold	50	16	Adam	VGG16	0.58	0.38	0.52	0.5000	0.51

2	503+ aug train 3x/gambar k-fold	50	16	Adam **lr 0.001**	CNN	0.12	0.49	0.00	0.4320	0.33
		50	16	Adam **lr 0.00005**	VGG16	0.62	0.54	0.29	0.4800	0.50

Based on table 1 of the model training results with 60:25;15 split data above, the VGG16 model shows greater stability and more balanced performance across all classes compared to the CNN model. In the VGG16 model the F1-Score achieved is higher and more consistent, showing a smaller performance gap between categories. In a dataset scenario involving 503 images with triple augmentation per image and K-Fold Cross Validation, VGG16 recorded the highest F1-Score in Class 1 (0.62), while maintaining relatively stable scores in the other two classes (0.54 and 0.29). In contrast, the CNN model showed greater class imbalance, with lower F1-Score in certain categories. As a result, VGG16 is considered more reliable and more suitable for integration into web-based detection systems. The interpretation and evaluation process was carried out by analyzing the accuracy and loss metrics, confusion matrices, and model performance tests, with the training performance graphs for both models presented in Figure 1 and Figure 2 below.

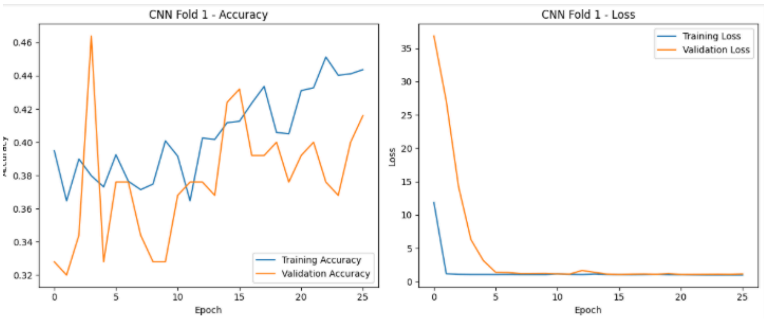

Figure 1. Accuracy and Loss Graphs of the CNN Model

Based on Figure 1, the accuracy and loss graphs of the CNN model indicate that the model's learning curve remained unstable throughout the training process, reflecting inconsistent learning performance and suboptimal convergence in classifying the three categories.

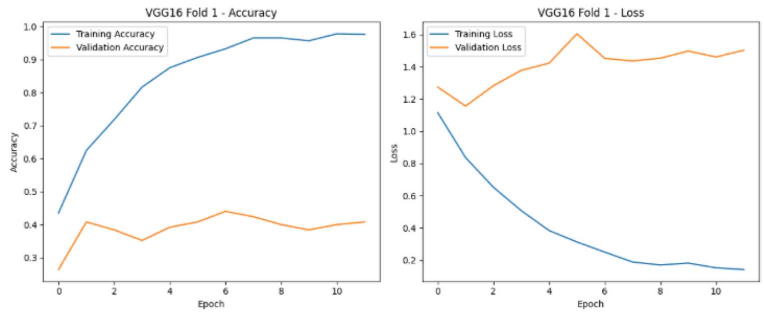

Figure 2. Accuracy and Loss Graphs of the VGG16 Model

Based on Figure 2, the accuracy and loss curves of the VGG16 model suggest that the model quickly memorized the training data patterns but failed to generalize effectively to the validation set, indicating signs of overfitting. The confusion matrices of the two models are presented in Figure 3 and Figure 4 below.

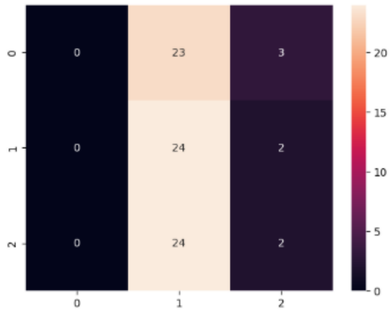

Figure 3. Confusion Matrix of the CNN Model

Based on Figure 3, the confusion matrix of the CNN model shows a tendency for the model to concentrate its predictions within a single class, indicating poor classification performance across the other categories.

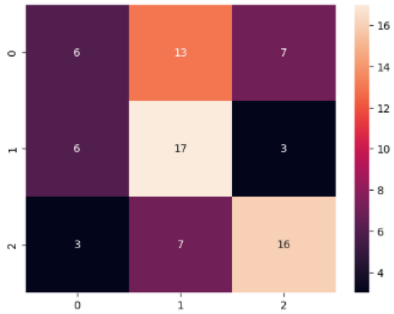

Figure 4. Confusion Matrix of the VGG16 Model

In contrast, as shown in Figure 4, the confusion matrix of the VGG16 model demonstrates a more balanced distribution of predictions across all classes, reflecting better classification consistency and generalization capability. The evaluation of the best performing models is shown in Table 2 below.

Table 2. Model Performance Evaluation Results

Model	Test Accuracy	F1-Score
CNN	0.4320	0.33
VGG16	0.4800	0.50

Based on table 2 for the evaluation results, the VGG16 model achieved an F1-Score of 0.50 and an accuracy of 0.4800, outperforming the CNN model, which obtained an F1-Score of 0.33 and an accuracy of 0.4320. Based on this performance, VGG16 was selected as the primary model for integration into the web-based dirty bowel disease detection system.

The development of this web-based application followed the Rapid Application Development (RAD) framework, consisting of three phases: Requirement Planning, Design, and Implementation. In the Requirement Planning phase, user needs were analyzed, focusing on individuals concerned with digestive health, with core features including image import for diagnosis and information about dirty bowel disease and related conditions. The Design phase, based on these requirements, involved creating system flow diagrams such as use case diagrams, activity diagrams, sequence diagrams, state diagrams, class diagrams, and user interface mockups. In the Implementation phase, the entire system design was successfully realized using the Flask web framework and Python programming language. The application was equipped with various key features, including a homepage, image upload functionality for palm-based detection, pages containing disease information, displays for classification results of dirty bowel disease, other diseases, and healthy palm conditions, as well as additional health information related to constipation, heart health, and immunity. To ensure system functionality and reliability, testing was carried out using both white box and black box approaches. White box testing was conducted using the basis path method to verify the accuracy of the system's internal logic, particularly for the image import and disease information display features. The test results confirmed that all expected functions operated successfully without errors, indicating that both the image import and information display features passed the white box testing phase according to the planned design.

Subsequently, black box testing was implemented on multiple devices with different hardware specifications to evaluate the consistency of system performance across varied usage environments. The testing outcomes showed that all system features operated properly on all tested devices, ensuring compatibility and responsiveness. Additionally, an analysis test was conducted to assess the system's detection feature in classifying palm images into dirty bowel disease, other diseases, and healthy palm categories. The results demonstrated that the detection feature functioned consistently and accurately across the different devices tested. The prediction process yielded an average confidence score of 48.89% using the trained VGG-16 model, with each image category successfully classified. These findings indicate that every testing method applied — both functional and performance tests — achieved the desired outcomes, confirming that the detection system was well-developed, reliable, and ready for practical use in providing accessible health screening services for the community.

CONCLUSION

This study concludes that the palm image classification models based on Convolutional Neural Network (CNN) and VGG16 architectures demonstrate promising performance in detecting intestinal health disorders. Among the two, the VGG16 model consistently outperformed the CNN model, achieving a higher and more balanced F1-score of 50% compared to CNN's 33%, particularly when utilizing data augmentation via ImageDataGenerator and validation through K-Fold Cross Validation on the latest dataset. The implementation of a web-based detection system using Flask, HTML, CSS, and Bootstrap also proved to be responsive, user-friendly, and capable of providing real-time prediction results, displaying disease categories and confidence scores with an average confidence value of 48.89% across three classes. To further improve this research, it is recommended to increase dataset size and category variations, annotate key palm areas for more focused detection, compare with alternative algorithms, involve multiple herbal therapy practitioners in the labeling process to enhance objectivity, and incorporate additional relevant secondary data to enrich the dataset and reduce the risk of overfitting. Additionally, integrating a real-time image capture feature within the web application is suggested to enable users to directly capture and analyze images through device cameras during the detection process.

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