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Innovation of Early Detection System for Vannamei Shrimp Disease Using Integration of MobileNet-V3 Architecture and K-Nearest Neighbors Algorithm

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ABSTRACT

Vannamei shrimp (Litopenaeus vannamei) cultivation is an important sector of the fisheries industry. However, it is vulnerable to diseases such as White Spot Syndrome Virus (WSSV), Bacterial Gill (BG) disease, and the combined infection White Spot Syndrome Virus and Bacterial Gill (WSSV_BG) disease, all of which can result in substantial economic losses. Early disease detection is essential, yet conventional approaches—including visual inspection and laboratory testing—are often limited by time, cost, and diagnostic accuracy. This study aims to develop a digital image-based early-detection system for shrimp diseases by integrating the MobileNet-V3 architecture as a feature extractor and the K-Nearest Neighbours (KNN) algorithm as a classifier. MobileNet-V3 was chosen for its ability to extract image features accurately and efficiently, while KNN is used as a classifier, requiring no retraining. The combination of the two produces an image classification system suitable for real-time implementation on resource-constrained devices, unlike previous studies that rely entirely on deep learning. The dataset consists of four categories of shrimp conditions (healthy, BG, WSSV, BG_WSSV) obtained from field documentation and collaborative sources. The processing pipeline includes image preprocessing, data augmentation, feature extraction using pretrained MobileNet-V3, and classification with KNN using Euclidean distance and a weighting scheme. Experimental results demonstrate strong performance, achieving 92% accuracy, 91.5% precision, 91.1% recall, and 91.1% F1-score. Compared with baseline models like MobileNet-V3–Softmax and conventional Convolutional Neural Networks (CNNs), the proposed approach performs better, especially in data-limited scenarios. These findings demonstrate the potential of integrating deep learning and classical machine learning to support lightweight, accurate, and adaptive mobile-based diagnostic systems for field deployment.

1. INTRODUCTION

The cultivation of shrimp, in particular Litopenaeus vannamei (shrimp), plays a strategic role in the national and global fisheries sector [1-3]. Indonesia is one of the largest exporters of shrimp in the world [4], with marked exports reaching USD 2.16 billion in 2023 [5], and the target is to increase by up to 250% by 2024 [6]. The vannamei commodity accounts for around 75% of total national shrimp production [7, 8]. However, productivity and sustainability commodities are very vulnerable to diseases such as White Spot Syndrome Virus (WSSV) [6-8], Early Mortality Syndrome (EMS) [9-11], and Infectious Hypodermal and Haematopoietic Necrosis Virus (IHHNV) [12-14], as well as other diseases [15-17]. Infection can cause death, with mass casualties even reported to reach 100% if not handled quickly [18], with estimated economic losses cumulative in the Asian region exceeding USD 1 trillion [19]. In Indonesia, various centre cultivation also reported losses of hundreds of millions of rupiah due to epidemic disease [20]. Practice field detection is still dominated by manual visual observation and/or laboratory tests, which are reactive, time-consuming, and inefficient in terms of cost and resource use [21]. This leads to an increased risk of late diagnosis, wider disease spread, and significant losses for cultivators.

Given the challenge mentioned, it is necessary to detect shrimp disease early, accurately, reliably, and applicable to vannamei in operational pond environments. The issues raised in the study. This is how designing a system for detecting disease in digital images that not only identifies disease quickly and precisely, but also provides information and recommendations for supporting decision-making at the cultivation level. For that, the research proposes integrating the Convolutional Neural Network (CNN) MobileNet-V3 [22] architecture as a feature extractor with the K-Nearest Neighbours (KNN) [23] algorithm as a classifier. MobileNet-V3 was selected for its efficiency, competitive compute performance, and performance on devices with limited power, such as smartphones and edge devices [24-26]. On the other hand, KNN offers simple nonparametric classification, is effective on non-linear data, is relatively robust to variations in class distributions, and is easy to implement [27-29]. This integration is intended to produce an accurate, lightweight, and ready system for a wide range of fields.

The combination of MobileNet-V3 CNN as a feature extractor with the KNN classifier can achieve high performance [30]. This achievement indicates that the features generated by MobileNet-V3 can represent visual characteristics more compactly and discriminatively, making it easier for KNN to distinguish between classes in the feature space. The advantages of MobileNet-V3, which uses a depthwise separable convolution architecture, squeeze-and-excitation, and a non-linear activation (h-swish) mechanism, produce more informative and stable features than conventional CNNs [31]. When these features are classified using KNN, the classification process tends to be more effective because KNN can leverage the proximity between feature vectors that are well-structured by MobileNet-V3. Conventional CNNs show that basic architectures without optimisations such as depthwise convolution, bottleneck blocks, or attention modules are unable to produce features sufficiently representative for complex classification [32]. Conventional CNNs are also more prone to losing important information through pooling operations and are less efficient at capturing visual variations and global spatial relationships [33]. As a result, both the feature extraction process and the classification stage are suboptimal, resulting in lower performance than MobileNet-V3.

Meanwhile, the MobileNet-V3 + Softmax combination outperforms the Conventional CNN but not the MobileNet-V3 + KNN CNN. This is because Softmax relies on the linearity of the decision boundary in the output layer. Softmax tends to be suboptimal when the feature distributions across classes are not perfectly linearly separable [34]. In other words, although MobileNet-V3 can provide a good feature representation, Softmax is not always able to capture the complexity of the relationships among those features, especially when the class distribution is non-linear.

As progress in computer vision continues, studies have shown the potential for detecting diseases in shrimp using image-based methods. The SHRIMPAI mobile application, for example, utilizes CNNs for WSSV detection in the field, achieving accuracy up to 99% and specificity of 98.9% [35]. Edge–machine learning approaches have also been proposed for WSSV monitoring using MobileNet-V3–Small and EfficientNetV2B0 architectures, reporting F1-scores of 0.72 and 0.99, respectively, while highlighting issues of data imbalance and the need for efficient inference on-device [36]. In the related domain, the integration of MobileNet-V3 into framework detection (MobileNet–CAYOLO) shows accuracy around 92%–93% with good parameter efficiency on the edge [37], strengthening the relevance of a lightweight architecture for image-based application detection. In the context of vannamei, other studies demonstrate the utilization of CNN for the detection of disease LeNet [38], detection of existence, quantification, and measurement size shrimp in the pond [39], detection of disease with YOLOv5 [40], classification results cultivation [41], detection size [42], and calculation of fry [43]. Outside image: approach-based profiles of fatty acids are also used to distinguish between freshwater and seawater growth media [44]. Meanwhile, KNN has been reported to be beneficial for WSSV classification in vannamei [45], classification of shrimp samples based on Bbf concentration [46], and assessment of pond water quality. In general, corpus study. This confirms the effectiveness of CNN in extracting visual features and the feasibility of KNN for task classification in aquaculture.

Despite this, there are still relevant gaps. The majority of studies use conventional CNN architecture or real-time detectors (e.g., YOLOv5), which are relatively heavy in a way computing [38-43], so that less than optimal for implementation wide on mobile/edge devices in the pond [36, 37]. On the other hand, although KNN has been applied to several task-related [45, 46] applications, integrating systematic MobileNet-V3 as an extraction backbone with KNN as a classifier for multi-class detection of disease in shrimp vannamei based images. Not yet reported in a way adequate in the literature we reviewed. Thus, the novelty and state-of-the-art position of the research lie in the integration of the lightweight CNN, MobileNet-V3 [24-26]. With KNN [27-29], a system detection is produced that is accurate, efficient, and early in computation, and practical for operation in the field.

Unlike previous studies, which were entirely based on deep learning (CNN and YOLO) and directly processed images for classification, this study uses a hybrid model. This model uses deep learning only for image feature extraction, which is converted to a numeric vector. These feature vectors are then classified using a data mining KNN algorithm. This separation-based approach results in a faster, more computationally efficient classification process.

In line with the research background and identified research gaps, this study aims to develop and evaluate an early disease detection system in Litopenaeus vannamei shrimp by integrating MobileNet-V3 and the KNN algorithm. The proposed system is expected to improve classification accuracy and consistency under heterogeneous field data conditions.

2. RESEARCH METHODS

2.1 Research design

This research uses a quantitative experimental approach with a digital image-based detection system development method. The goal is to build a classification model for vannamei shrimp disease by integrating the MobileNet-V3 deep learning architecture as a feature extractor and KNN as a classification algorithm. Validation is performed using evaluation metrics such as accuracy, precision, recall, and F1-score.

2.2 Research stages

The method used in this study is the integration of MobilNet-V3 with KNN. MobilNet-V3 is a CNN architecture specifically designed for mobile devices with optimizations for inference speed and computational efficiency [47]. Meanwhile, KNN is a simple machine learning algorithm that classifies data based on proximity (distance) to training samples [48]. The integration of MobilNet-V3 with KNN was carried out by utilizing MobilNet-V3 as a visual feature extractor used to identify disease patterns in white shrimp, such as white spots, discoloration of the gills, and others. The results of MobilNet-V3 were classified using KNN to determine disease diagnoses based on proximity to the training sample data through optimizing the k-value parameters (3, 5, and 7) and distance matrix to overcome the limitations of the available data and class imbalance. The following is the flow of the research methodology carried out:

2.2.1 Dataset acquisition

The vannamei shrimp image collection in this study covers four condition categories: healthy shrimp, shrimp infected with BG, WSSV, and shrimp with a combined BG and WSSV infection (BG_WSSV). The image dataset was obtained through several sources, including collaborations with farmers or aquaculture laboratories, the use of public datasets, and direct field documentation using a high-resolution smartphone camera. A partial display of the dataset used can be seen in Figure 1.

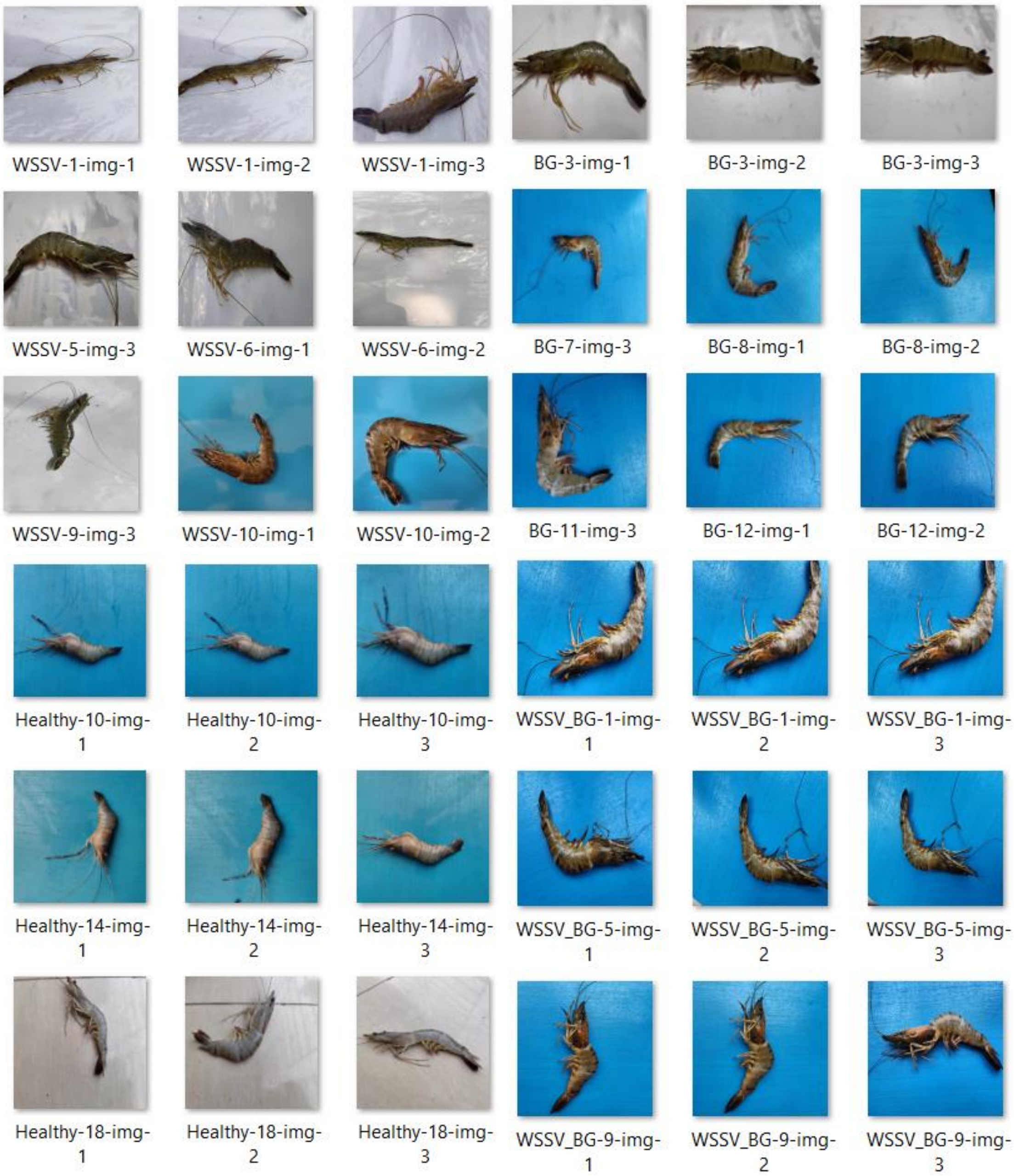

Figure 1. Dataset

Next, the dataset was distributed evenly in terms of quantity. The distribution of the dataset used can be seen in Figure 2.

2.2.2 Image labeling and preprocessing

The labeling process was carried out by classifying each image based on the shrimp's condition, namely, between healthy and infected shrimp. Next, image preprocessing was carried out to prepare the data to suit the needs of the MobileNet-V3 model. This preprocessing included resizing the images to 224 × 224 pixels, normalizing pixel values to a 0–1 scale, and data augmentation through rotation, flipping, and brightness adjustments. This augmentation aimed to balance the distribution between classes and enrich the diversity of the training data.

2.2.3 Feature extraction with MobileNet-V3

The MobileNet-V3 architecture, both the Large and Small versions, was used as a feature extractor in this study. The model was pre-trained on the ImageNet dataset, with the final classification layer (fully connected layer) removed to focus the model's function as a feature extractor. The processed images were then passed through this model, and the final features generated from the bottleneck layer were extracted and stored in vector form as a representation of each image.

The following is a visualization of the MobileNet-V3 CNN stages.

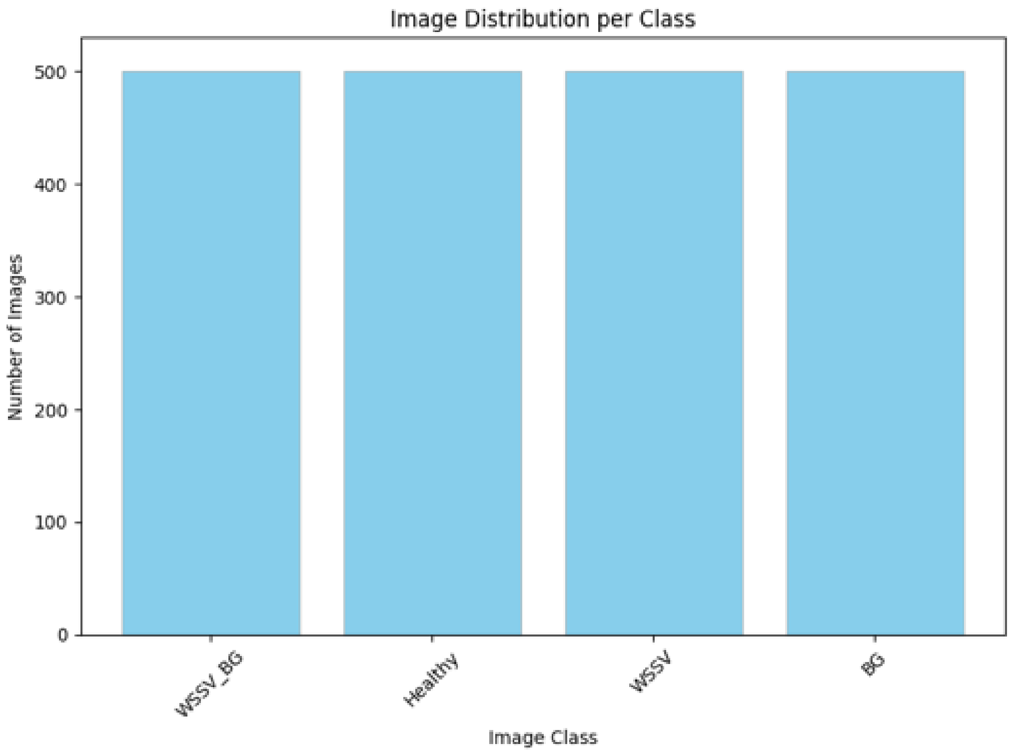

Figure 2. Dataset distribution graph

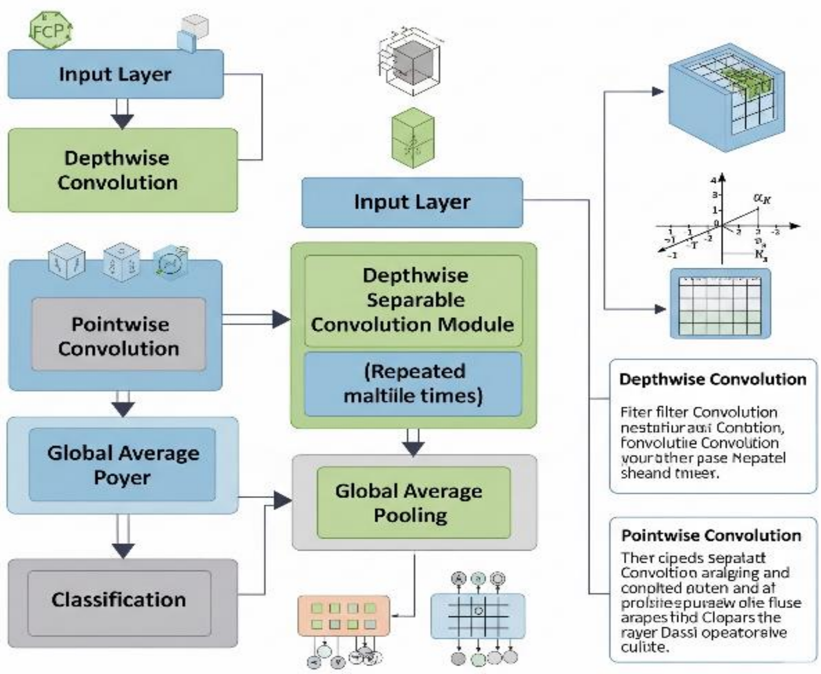

Figure 3. MobileNet-V3 Convolutional Neural Network (CNN) stages

Figure 3 shows the stages of the proposed system architecture, which consists of two main phases: feature extraction and classification [49, 50].

1) MobileNet CNN Phase (Feature Extraction)

- Input Image: The process begins by feeding the raw image into the model.
- Depthwise Separable Convolutions: This is a key component of MobileNet, which divides standard convolution into two stages: Depthwise Convolution (applying one filter per input channel) and Pointwise Convolution (a 1 × 1 convolution to concatenate the outputs). This technique significantly reduces the computational burden and the number of parameters.
- Feature Maps: The network processes the image through recurrent convolution modules to generate feature maps that represent the image's important characteristics.
- Global Average Pooling (GAP): Before classification,

global average pooling is performed to reduce the dimensionality of the data and convert the feature maps into a single feature vector (the extracted feature).

2) KNN Classifier Phase (Classification)

- Extracted Features: The feature vector generated by MobileNet is used as input to the KNN algorithm.
- K-Nearest Neighbors (KNN): The KNN workflow is illustrated by finding the nearest neighbors (symbols 'K', 'C', 'N') around the test data (star symbols) based on the distance metric.
- Classification Output: The final class is determined based on the majority label of these nearest neighbors.

An outline of the stages of the MobileNet-V3 + KNN CNN combination can be seen in Figure 4.

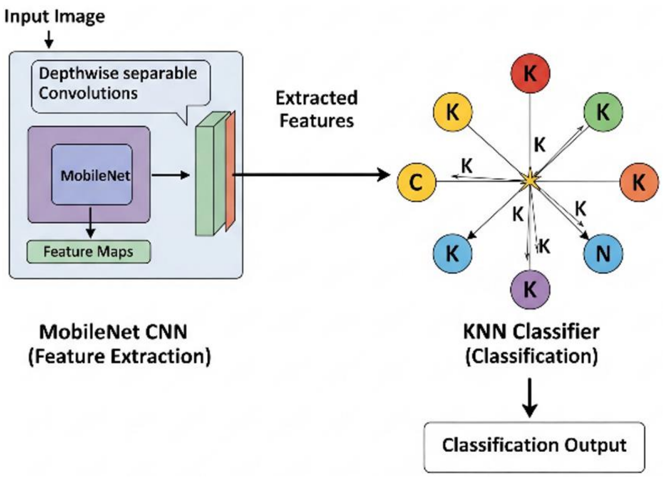

Figure 4. Convolutional Neural Network (CNN) MobileNet-V3 + K-Nearest Neighbours (KNN) stages in outline

2.2.4 Classification with the K-Nearest Neighbours (KNN) algorithm

The features extracted from the MobileNet-V3 architecture are then used as input for the KNN algorithm. Determining the best k-value is done through a cross-validation process for adaptive k-values by testing several candidate values [51], such as k ranging from 1 to 20. In addition, to improve accuracy, we calculate the weights on the nearest neighbors, while to measure the similarity between feature vectors, the Euclidean distance calculation method is used as a basis for determining the closeness between images. The following is a visualization of CNN MobileNet-V3 + KNN.

2.2.5 Model evaluation and validation

The dataset was divided into two parts: training data and test data, with common proportions such as 80:20, 70:30, and 90:10 to ensure fair and representative model evaluation. Model performance was evaluated using several classification metrics, including accuracy, precision, recall, and F1-score, to provide a comprehensive overview of the prediction performance. Furthermore, a confusion matrix analysis was performed to identify patterns of misclassification between classes. For comparison, model performance was also compared with baseline approaches, such as MobileNet-V3 directly combined with the Softmax classification function, and conventional CNN architectures.

The data preprocessing and augmentation processes in this study were carried out systematically to ensure the model obtained sufficient training data and met experimental reproducibility standards. All images were first resized to 224 × 224 pixels using bilinear interpolation, then normalized to the range 0–1 by dividing the pixel value by 255. To increase data diversity, geometric and photometric transformation-based augmentation was performed, including random rotation of ±15°, horizontal flip with a probability of 0.5, random zoom in the range 0.9–1.1, and brightness adjustment of ±20%. This augmentation was applied on-the-fly so that each image had the opportunity to undergo a different transformation at each training epoch. After the images underwent feature extraction by MobileNet-V3, the resulting feature vectors were normalized using a z-score based on the mean and standard deviation of the training set. L2 (unit norm) normalization was then applied to maintain the stability of the distance calculation between features before being used as input to the KNN algorithm.

In the classification stage, KNN uses the Euclidean distance metric as the primary measure of closeness between features. The Euclidean distance was chosen based on the characteristics of MobileNet-V3 features, which are continuous and have undergone a standardization process, ensuring that each feature dimension contributes equally to the distance calculation. Furthermore, Euclidean has low computational complexity and has proven effective in various CNN feature-based studies, making it a relevant choice for small- to medium-scale datasets. To improve performance and reduce sensitivity to relatively distant samples [52], this study implemented an inverse-distance weighting scheme, where the weight of each neighbor is calculated using the function Eq. (1):

$$\omega_i = 1/(d_i + \epsilon) \tag{1}$$

with the value shown in Eq. (2):

$$\epsilon = 1 \times 10^{-5} \tag{2}$$

To prevent division by zero. This scheme gives greater influence to the nearest neighbors, which are geometrically more representative of the test sample. Additionally, alternative weighting methods, such as Gaussian weighting, are shown in Eq. (3):

$$\omega_i = e^{-d_i^2 \, 2\sigma^2} \tag{3}$$

to assess the model's sensitivity to variations in the weight function, with the σ parameter set based on the average distance between training samples.

The k-value for KNN was selected through a stratified 5-fold cross-validation process to ensure that the class distribution remained proportional across each fold. The k-values tested ranged from 1 to 20, and the best value was selected based on the highest average F1-score on the validation data. If several k-values showed relatively similar performance, a lower value was chosen to avoid unnecessary increases in complexity. All models were then evaluated using standard metrics, including accuracy, precision, recall, and F1-score, as well as a confusion matrix to identify patterns of misclassification between classes.

2.3 Developer tools and devices used

The system is implemented using the Python programming language with support for deep learning frameworks such as TensorFlow/Keras or PyTorch. Additional libraries include Numpy, which plays a key role in numeric array manipulation, such as image conversion and normalization in the form of pixel matrices, and serves as a standard input format for deep learning models. Pandas is used to manage image metadata, such as class labels, file names, and category information, in the form of structured tables, facilitating the integration of image data and labels during model training and evaluation. Scikit-learn is used for model evaluation, and Matplotlib is used for visualization and manipulation of numeric data. The model training and testing process is run on hardware in the form of a computer equipped with a GPU (GTX1070) or using cloud computing services such as Google Colab or AWS for efficiency. For field testing purposes, an Android smartphone is used to simulate the implementation of a mobile-based detection application.

2.4 Advanced development plan (optional)

As a next step, the developed model was integrated into a mobile application to support real-time shrimp disease detection in the field. Field trials were conducted with farmers to validate the system's performance under real-world conditions, while also assessing its usability and detection accuracy in an operational environment. In the future, the system has the potential to be further developed with additional features such as multi-disease detection, segmentation of affected shrimp body parts, and heatmap visualization to more informatively show the location of disease indications on the shrimp body.

3. RESULTS AND DISCUSSION

3.1 Feature extraction results

After image preprocessing and augmentation, the entire dataset is passed through the MobileNet-V3 architecture (Large version) for feature extraction. Each image generates a fixed-dimensional feature vector from the bottleneck layer, which is then used as input to the KNN algorithm. This process successfully reduces the image dimensionality to a lighter numerical representation while still containing relevant visual information.

3.2 Classification experiments with K-Nearest Neighbours (KNN)

Classification experiments were conducted using KNN with varying k-values from 1 to 20, both with and without distance weighting. Cross-validation results showed that the optimal k-value ranged from 1 to 5, depending on the distribution of the training and test data. The use of distance-based weighting showed a consistent increase in accuracy compared to the uniform approach, especially in cases of imbalanced data.

The selection of the k-value in the KNN algorithm plays a crucial role in classification performance. The k-value determines the model's level of generalization to the data. Too small a k-value can cause the model to be sensitive to noise (overfitting), while too large a k-value can blur the boundaries between classes (underfitting). Experimental results show that determining the optimal k-value balances model complexity and predictive accuracy, thereby improving classification performance stability. Thus, the k parameter is not merely a technical variable but a crucial component that influences the model's ability to scientifically and empirically represent data distribution patterns.

3.3 Model performance evaluation

Evaluasi performa dilakukan terhadap beberapa skenario dataset division, namely 70:30, 80:20, and 90:10. The test results in the best scenario (90:10) produced the following performance:

Table 1. Model performance evaluation

Evaluation Metric	Value (%)
Accuracy	92.00
Precision	91.50
Recall	91.10
F1-Score	91.10

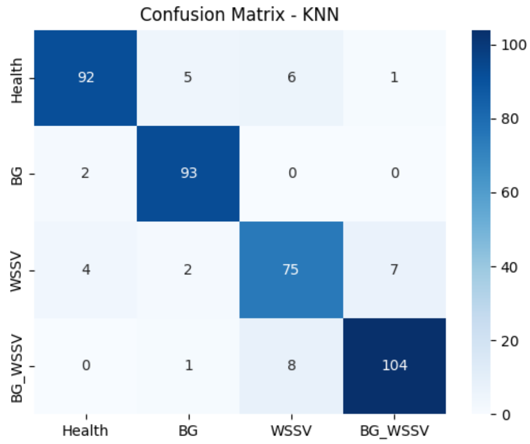

Figure 5. The confusion matrix results from the experiment

Evaluation results in Table 1 show that the integration of MobileNet-V3 with KNN is capable of classifying shrimp conditions with a high degree of accuracy. Confusion matrix analysis shows that most misclassifications occur between the BG and BG_WSSV classes, which share significant visual similarities. Meanwhile, the confusion matrix can be seen in Figure 5.

The "Health" row represents data that are actually healthy. The total healthy data is 92 + 5 + 6 + 1 = 104 samples. 92 samples are actually healthy and predicted as "Health" (True), 5 samples are actually healthy but predicted as "BG" (False), 6 samples are actually healthy but predicted as "WSSV" (False), and 1 sample is actually healthy but predicted as "BG_WSSV" (False).

The "BG" row represents data that are actually infected with "BG". The total BG data is 2 + 93 + 0 + 0 = 95 samples. 93 samples are actually "BG" and predicted as "BG" (True), while 2 samples are actually "BG" but predicted as "Health" (False).

The "WSSV" row represents data that are actually infected with "WSSV". The total WSSV data is 4 + 2 + 75 + 7 = 88 samples. 75 samples are actually "WSSV" and predicted as "WSSV" (True). 7 samples were actually WSSV but predicted BG_WSSV (False).

The "BG_WSSV" row represents data actually infected with both BG and WSSV. The total BG_WSSV data is 0 + 1 + 8 + 104 = 113 samples. Of these, 104 samples were actually

BG_WSSV and predicted BG_WSSV (True), and 8 samples were actually BG_WSSV but predicted WSSV (False).

3.4 Comparison with baseline

For comparison, classification experiments were conducted using MobileNet-V3 directly combined with a fully connected layer and the Softmax activation function, as well as a conventional CNN model. The comparison results are shown in the following Table 2.

Table 2. Comparison with baseline

Model	Accuracy (%)
CNN MobileNet-V3 + KNN	92.00
CNN MobileNet-V3 + SoftMax	89.50
CNN Konvensional	87.00

From these results, the feature extraction approach using MobileNet-V3 combined with KNN shows advantages in terms of accuracy and generalization, especially on limited data amounts.

3.5 Discussion

The results show that the integration of MobileNet-V3 as a feature extractor and KNN as a classification algorithm can provide excellent detection performance for shrimp diseases based on digital images. The feature extraction process from the bottleneck layer of MobileNet-V3 successfully represents images into low-dimensional yet informative numeric vectors, enabling efficient classification without complex training. KNN classification experiments with varying k-values demonstrate that the use of distance weighting is superior to uniform weighting, especially in addressing data imbalance between classes. This indicates that the influence of distance between features in the vector space has a significant impact on classification quality. Model evaluations at different data sharing ratios show that the 90:10 ratio provides the best results, with an accuracy of 92%, an F1-score of 91.1%, and consistent performance in other metrics. Test results show that the combination of the MobileNet-V3 CNN as a feature extractor and the KNN algorithm as a classifier provides the highest performance, with an accuracy of 92.00%. This achievement indicates that the features generated by MobileNet-V3 are able to represent visual characteristics more compactly and discriminatively, making it easier for KNN to distinguish patterns between classes in the feature space. MobileNet-V3's advantage, which utilizes a depthwise separable convolution architecture, squeeze-and-excitation, and a non-linear activation (h-swish) mechanism, produces more informative and stable features than conventional CNNs. When these features are classified using KNN, the classification process tends to be more effective because KNN can exploit the proximity between feature vectors, which are well-structured by MobileNet-V3.

Compared to baselines such as MobileNet-V3–Softmax and conventional CNNs, the MobileNet-V3–KNN approach demonstrates superior accuracy and generalization on limited datasets, confirming the effectiveness of this hybrid approach in the context of edge computing. This can be seen in the graph in Figure 6. However, this system still faces challenges in distinguishing between combined conditions (BG_WSSV), which visually share a high similarity to a single class (BG or WSSV). Misclassification errors in this area suggest the need for additional approaches, such as shrimp body part segmentation or the integration of ensemble learning techniques, to improve sensitivity to various infections. These findings provide a strong basis for suggesting that combining lightweight deep learning models and classical classification algorithms can be an effective solution for real-time shrimp disease detection, which is resource-efficient and easy to implement on mobile devices in the field. The combination of MobileNet-V3 + Softmax achieved an accuracy of 89.50%, slightly lower than KNN. This occurs because Softmax relies on the linearity of the decision boundary in the output layer. Softmax tends to be suboptimal when the feature distribution between classes is not completely linearly separable. In other words, although MobileNet-V3 is capable of providing a good feature representation, Softmax does not always capture the complexity of the relationships between these features, especially if the class distribution is non-linear.

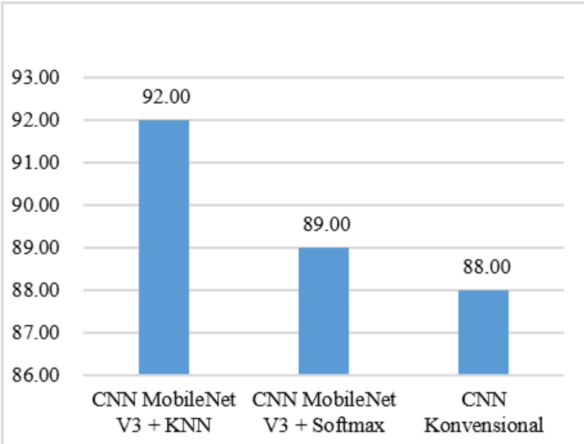

Figure 6. Comparison of accuracy results

On the other hand, a conventional CNN only achieved an accuracy of 87.00%, which is the lowest score in this test. This indicates that a basic CNN architecture without optimizations such as depthwise convolution, bottleneck blocks, or attention modules is unable to produce features representative enough for complex classification. Conventional CNNs are also more susceptible to losing important information due to pooling operations and are less efficient at capturing visual variations and global spatial relationships. As a result, both the feature extraction and classification stages are suboptimal, resulting in model performance that is not as good as MobileNet-V3. Overall, these results confirm that the use of a more sophisticated feature extraction architecture, such as MobileNet-V3, has a significant impact on improving the quality of image representation. Furthermore, the choice of classification algorithm also influences the final performance. KNN proved to be more adaptive in utilizing the non-linear feature structure generated by MobileNet-V3, allowing for more accurate mapping of feature variations and proximity between classes compared to Softmax or conventional CNNs directly. These findings confirm that integrating modern CNN architectures with appropriate traditional classifiers can yield substantial and consistent performance improvements.

4. CONCLUSION

This research successfully developed an early disease detection system for Litopenaeus vannamei shrimp by integrating the MobileNet-V3 architecture as a feature extractor and the KNN algorithm as a classifier. This combination achieved superior classification performance, with a peak accuracy of 92% and an F1-score of 91.1%. MobileNet-V3 effectively extracts representative and compact image features, while KNN provides a lightweight classification mechanism without requiring retraining, making it ideal for real-time systems on resource-constrained devices such as smartphones.

Experimental results show that the MobileNet-V3–KNN approach outperforms baseline methods such as MobileNet-V3–Softmax and conventional CNNs, especially in scenarios with limited training data. The application of image augmentation and distance weighting in KNN has been shown to improve the model's resilience to class imbalance and reduce the risk of prediction bias. However, the system still has limitations in distinguishing cases of combined infections (e.g., BG_WSSV), indicating the need to improve the model's ability to understand multi-label patterns and more complex spatial features.

For further research, it is recommended to apply the feature fusion method between MobileNet-V3 and an attention-based network architecture to enrich the extracted visual information. Furthermore, integration with adaptive ensemble learning or graph-based KNN can be explored to improve the classification of overlapping data. Overall, this research provides a significant scientific contribution by demonstrating the effectiveness of a combination of lightweight deep feature extraction and instance-based classification for aquaculture disease detection. This approach is not only computationally efficient but also opens new directions in the development of computer vision-based intelligent systems that can be practically implemented in the digital fisheries sector.

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