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Model Performance Evaluation: VGG19 and Dense201 for Fresh Meat Detection

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Abstract: To guarantee consumer safety and meet quality expectations, accurate detection of meat quality is a critical component of the food industry. The objective of this research endeavor is to assess and contrast the fresh meat detection capabilities of two distinct artificial neural network architectures, denoted as Dense201 and VGG19. Automated systems that can identify vital qualities in fresh meat, including color, texture, and cleanliness, have become feasible due to the development of image processing technology. For this reason, however, there are still few direct comparisons between various architectures of artificial neural networks, particularly VGG19 and Dense201. Comparing and contrasting the performance of both models in identifying the quality of meat from visual images, this study attempts to fill this void. Utilizing a vast dataset containing a variety of fresh meats exhibiting substantial visible variations constituted the research methodology. The assessment was conducted by examining the efficacy of both models in determining the quality of meat using established performance metrics, including accuracy, precision, recall, and F1-score. Regarding the detection of fresh meat, it is anticipated that the findings of this study will offer a comprehensive understanding of the benefits and drawbacks associated with every artificial neural network architecture. Contributing to a greater comprehension of the application of precise and efficient meat detection technology, this study also furnishes the food industry with a foundation for determining which model best meets the requirements of meat quality detection on a larger production scale.

Keywords: Dense201; Food Industry; Meat Quality; Neural Network; VGG19

INTRODUCTION

The contemporary demand for meat has undergone substantial transformations in tandem with shifts in consumption patterns, lifestyle choices, and the recognition of the critical nature of nutrition. In response to the expanding global population and more and more, the significance of eating a healthy, well-rounded diet is being recognized. There is a rising demand for premium animal products. Contemporary consumers are not solely interested in meat for its protein content; they also demand assurances of food safety and superior quality. In addition, the trend toward healthier lifestyles is increasing demand for organic, hormone-free, and sustainably raised animal products, among others. Aligned with this, there is a concurrent change in consumer inclinations toward meat origins derived from reputable and high-quality sources, wherein sustainability and ethical considerations are progressively gaining prominence. Additionally, meat industry innovation and technology contribute to the demand for meat products that are diverse, readily available, and simple to acquire. The progression of production, processing, and distribution techniques has facilitated consumers' access to a diverse

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range of meats in accordance with their individual preferences. Ensuring the safety and quality of meat, as well as its compliance with sustainability standards, is imperative to satisfy the present demands of consumers. As a result, the food industry, with a particular emphasis on the meat sector, persists in its endeavor to introduce novel products that not only fulfill nutritional requirements but also embody contemporary consumers' concerns regarding safety, quality, and sustainability.

Figure 1. Fresh meat
Source: Google Image

Figure 1, the quality of fresh meat has a central role in the food industry that cannot be ignored, considering its very significant impact on people's health and welfare. The demand for high-quality, fresh meat is rising in tandem with the growing recognition of the significance of nutritional factors and food safety. Contemporary consumers not only desire meat products that satisfy the standards of delectable flavor but also prioritize the safety aspects of food consumption. Nevertheless, the primary issue that frequently arises pertains to the challenge of precisely ascertaining whether meat remains fresh or has exceeded the suitable threshold for consumption. Contaminated or damaged meat can significantly jeopardize consumer health. Hence, the significance of precise identification of fresh meat with a notable degree of precision should be recognized, as it plays a pivotal role in upholding public health.

The application of image processing and associated technologies has been extensively employed in attempts to address this issue. Nevertheless, significant obstacles persist in visually discerning fresh meat. Visual imagery is a highly effective method for assessing the quality of meat. However, accurately distinguishing between meat that is still fresh and meat that is no longer safe to eat remains a challenge. The current level of advancement in meat detection technology has reached a stage where the utilization of artificial neural networks, such as VGG19 (Hindarto, 2023b), and Dense201 (Saputra et al., 2023), (Hindarto, 2023c), (Hindarto, 2023a), is becoming increasingly appealing. Nevertheless, there is a need for more comparisons between these two architectures, specifically in the context of fresh meat detection.

Precise identification of fresh meat not only affects the quality of the product in the food industry but also influences consumer well-being. Attaining a high degree of precision in assessing the quality of meat enables the prevention of the introduction of unsuitable products for consumption into the market.

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By utilizing advanced technology that can efficiently identify fresh meat, the potential hazards to consumer well-being can be significantly reduced. Therefore, paying attention to the need for reliable detection of fresh meat is essential to ensure that people can consume meat with confidence in its quality and safety. In addition, this aspect has significant ramifications for upholding quality standards in the food industry sector, given its crucial role in delivering safe and superior food products to consumers.

In the evaluation of the fresh meat detection performance of the VGG19 (Hindarto et al., 2023) and Dense201 (Saputra et al., 2023), models, two fundamental research inquiries are posed. Initially, the degree to which these two models can accurately distinguish between fresh and non-fresh meat according to the provided visual images. Furthermore, is there a substantial performance disparity between Dense201 and VGG19 regarding this detection task? It is anticipated that gaining a comprehensive understanding of the two models' capacities to identify and distinguish fresh meat will offer valuable insights into their dependability in the context of applications within the food industry.

The primary objective of this research endeavor is to furnish a comprehensive analysis of the merits and drawbacks associated with both the VGG19 and Dense201 models (Hindarto & Santoso, 2023) as they pertain to the detection of fresh meat. With any luck, this evaluation of model performance will serve as a foundation for the food industry to identify the most effective and dependable model for applications involving the detection of meat quality. Therefore, it is anticipated that this study will provide a substantial contribution to the development of precise meat detection technology, thereby ultimately enhancing consumer-accepted food safety and quality standards.

LITERATURE REVIEW

The objective of this literature review is to examine recent research on the detection of meat quality, explicitly focusing on comparing the Dense201 and VGG19 models. The literature review will look at a previous study that has tried to figure out what neural network models can and can't do when they must tell the difference between fresh and spoiled meat visually. This research employs deep learning (DL) to identify soliton waves in nonlinear transmission lines (NLTLs) automatically. Nine hundred images are acquired, and four classes of sine, square, triangle, and soliton waves are generated. Out of the five DL algorithms assessed, DenseNet201 exhibits the highest performance. This implies that it may be possible to employ DL algorithms for the automated detection of soliton waves, which could have far-reaching implications in disciplines such as physics, optics, nonlinear electronics, and telecommunications (Aksoy & Yigit, 2023). The study proposes the JutePestDetect model, which utilizes transfer learning, to detect jute pests promptly in Asian nations. Five pre-trained models and a dataset containing 380 images per pest class comprise the model. Our team tested how well the model worked by various metrics, including precision, recall, F1 score, ROC curve, and confusion matrix. The 99% accuracy of the customized regularized DenseNet201-based model provides an improved method for identifying pests in jute, which will benefit farmers around the world (Hasan et al., 2023). Transfer learning techniques and deep learning algorithms are used a lot in image sentiment analysis, which has become more popular. Image categorization works much better when you use a VGG-19-based approach that focuses on large body parts like the face. With an accuracy of up to 99%, this method can find and label emotions with different emotions using the CK+, FER2013, and JAFFE datasets (Meena et al., 2022). The Red Palm Weevil (RPW) is a big problem for palm trees, and there are a few good ways to find it right now. This paper suggests an excellent way to find things early on by recording and analyzing RPW sound activities. The method takes proper data and turns it into images. It then combines the pictures based on different features and uses Deep Learning to sort the images into groups of infected and uninfected images. The proposed method outperforms others in experiments conducted on public datasets (Boulila et al., 2023). Deep learning is essential for early plant species and disease identification in agriculture. Brassica Napus rapeseed species will be classified by their flowers, leaves, and packets in this study. Five CNN models were tested, and DenseNet201 classified both species with 100% accuracy for flowers and 97% for packets and leaves. These methods will be compared to metabolomics data in future studies (Alom et al., 2023). Globally, maize diseases reduce agricultural productivity and revenue. A new classification model classifies maize leaves as blight, common rust, gray leaf spot, and healthy using deep features and optimization strategies. The model classifies images using DenseNet201 and optimizes the SVM using Bayesian optimization. The model outperformed SVMs without deep

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features and optimization with 94.6% classification accuracy (Dash et al., 2023). This study uses USG images and deep transfer learning to determine fetal sex. A gynecologist labeled 4400 images. Fine-tuned convolutional neural networks, ft-DenseNet201, Logistic Regression, Linear Support Vector Machine, K-Nearest Neighbor, Decision Tree, Random Forest, and AdaBoost algorithms classified images. High accuracy values made this a new, automatic, and reliable fetal sex method (Sivari et al., 2024). The wide-ranging capabilities of deep learning have been demonstrated in numerous studies that have implemented DenseNet201 and VGG19 for meat quality detection and other purposes, including soliton wave identification, pest detection in plants, and image sentiment analysis. Nonetheless, a comprehensive comparison of these two models remains necessary. Further investigation is warranted to examine the integration of these models within domains, including meat quality detection, systems for early detection of pest attacks, and disease detection in plants. Additional investigation is required to refine the adaptation of these models across a multitude of particularized application domains.

METHOD

Research Method

A crucial initial stage in tackling the significant obstacles pertaining to meat quality detection in the food industry is the identification of the pertinent issues. To assess the state of the art in methodology, a comprehensive literature review was undertaken, with particular emphasis on the application of neural network models (e.g., VGG19 and DenseNet201) across different domains, with the aim of addressing the challenge associated with visually differentiating fresh from spoiled meat. This methodology was implemented prior to the subsequent critical step in this investigation, which entailed assembling a dataset comprising images of both new and spoiled meat from reputable sources (e.g., Kaggle) to guarantee sufficient representation of both classifications.

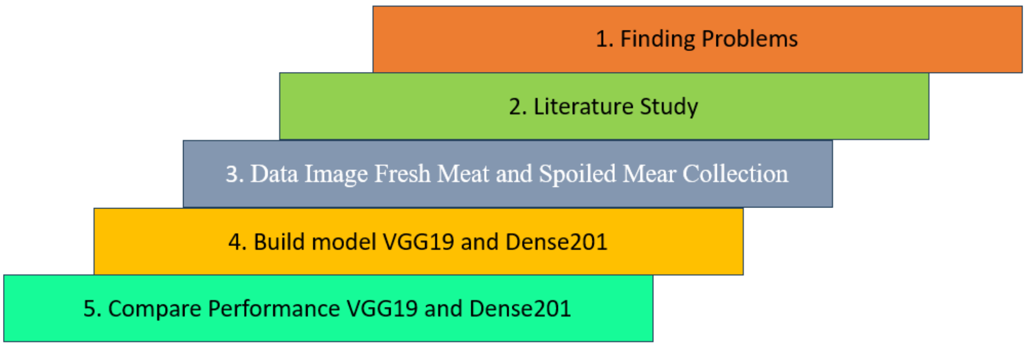

Figure 1. Proposed Method
Source: Property Researcher

Figure 1, the present study commenced by identifying pertinent challenges in the domain of meat quality detection, including the visual indistinguishability between fresh and spoiled meat. The initial phase entailed conducting a comprehensive literature review to gain insight into contemporary methodologies for utilizing neural network technology in applications such as image identification, with a specific emphasis on the VGG19 and DenseNet201 models. Following this, a dataset comprising images of fresh and spoiled meat was obtained from reputable sources (e.g., Kaggle) to ensure diversity and sufficient representation of both categories. The next step, following the collection of data, is to construct a model utilizing the DenseNet201 and VGG19 architectures. The procedure above consists of several stages: data loading, data cleansing (if required), data partitioning into training and test sets, and model configuration using suitable parameters. The model undergoes training utilizing a pre-existing dataset, during which it is provided with instructions to discern and classify fresh meat from spoiled meat.

In the concluding phase of this investigation, a performance comparison will be made between the two constructed models, VGG19 and DenseNet201. The assessment of model performance encompasses

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pertinent metrics, including accuracy, precision, recall, and F1 score. This comparison facilitates the evaluation of the efficacy and dependability of each model in visually distinguishing between fresh and spoiled meat. The findings of this comparison serve as a foundation for deriving conclusions regarding the suitability or superior performance of each model in the domain of meat quality detection. Additionally, they illuminate the possibility that future advancements may enhance the precision or efficacy of these models for applications involving meat quality detection.

Dataset Meat

The dataset in figure 2, meat dataset comprises two primary categories: fresh meat and spoiled meat. The dataset consists of 948 image files for each category, resulting in a total of 1896 image files for subsequent analysis and processing. The dataset originates from Kaggle, a prominent platform for sharing datasets across diverse domains of science and industry. The significance of this dataset resides in its potential utilization for the advancement of models or algorithms in image processing. By possessing a dataset that exhibits equilibrium between fresh and spoiled meat, researchers, data scientists, and developers can utilize this data to educate and evaluate image detection or classification algorithms. By employing deep learning methodologies such as VGG19 and Dense201, it is possible to construct a model that can accurately determine the freshness or spoilage of a piece of meat solely by analyzing the provided image.

This dataset can be utilized in the food industry, particularly in automated inspection systems, for the detection of meat that is no longer suitable for consumption. Moreover, this dataset can serve as a foundation for subsequent investigations pertaining to food preservation, waste administration, or even the creation of applications in the healthcare domain concerning the timely identification of ailments in meat. Nevertheless, it is crucial to bear in mind that handling datasets of this nature necessitates a comprehensive comprehension of data ethics and security, particularly regarding privacy and conscientious utilization. When utilized correctly, this dataset holds significant promise for fostering innovation in diverse domains pertaining to the applications of image processing in the food industry and health sectors.

Figure 2. Meat Dataset
Source: Kaggle dataset (Ulucan et al., n.d.)

VGG19

VGG19 (Li et al., 2023) is a renowned Convolutional Neural Network structure utilized in the field of image processing. Nineteen distinct levels make up the structure, precisely sixteen layers of convolution and three layers of fully connected, hence the name. The classification of fresh meat and rotten meat using the VGG19 method entails a sequence of intricate convolution and pooling operations. The convolution process is utilized to extract significant visual features from images precisely to distinguish between fresh and damaged meat. Each convolutional layer in VGG19 is designed to detect features at different levels of intricacy, ranging from basic features like edges and corners to more

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intricate features like texture and patterns associated with meat spoilage. The pooling process effectively decreases the dimensions of the extracted features while preserving crucial information. The final layers in the architecture are fully connected, serving to amalgamate the extracted features into a more abstract representation, which is subsequently employed for classification purposes. Within the framework of categorizing fresh and spoiled meat, VGG19 acquires the ability to distinguish visual patterns specific to each type of meat through a multi-level pattern recognition learning process. This enables the model to accurately determine whether an image represents fresh meat or if it has undergone deterioration.

The VGG19 model (Cuong et al., 2024) is characterized by its 19 layers, which are structured deeply. Its architecture employs a recurring concept, where convolution blocks are composed of multiple consecutive convolution layers, followed by a pooling layer that serves to decrease the dimensionality of the extracted features. The progressive deepening of layers in VGG19 enables the model to capture more intricate visual details, thereby facilitating the learning of abstract representations of meat images. Regarding meat classification, VGG19 possesses the capability to discern the visual distinctions between fresh meat and spoiled meat with a high level of precision. Higher convolutional layers in this architecture can identify physical changes associated with meat spoilage, such as color, texture, moisture, and other features. VGG19's capacity to precisely extract these characteristics enables it to distinguish between images of meat that remains in a satisfactory state and those that have incurred damage.

During the training phase, the VGG19 model acquires knowledge from a dataset comprising images depicting both fresh and spoiled meat. This procedure entails fine-tuning the weights and internal parameters within the model to enhance its capacity for accurately categorizing the images. VGG19 employs a backpropagation algorithm to iteratively modify these parameters by comparing the predicted outcomes with the actual labels until the desired level of accuracy in differentiating between the two meat categories is achieved. The VGG19 method for meat classification leverages the intricate and profound capabilities of this CNN architecture to comprehend and determine nuanced yet significant visual patterns between fresh and spoiled meat in images. Moreover, VGG19 employs a transfer learning methodology that capitalizes on pre-existing knowledge acquired from other extensive datasets. VGG19, by using pre-trained initial weights on a larger dataset, possesses the capability to identify common patterns in images, including visual characteristics that are valuable in discerning meat quality. The fine-tuning process involves modifying and optimizing these weights specifically to enhance the model's capability to discern meat quality, thereby improving its ability to classify fresh meat and spoiled meat.

Dense201

An innovative concept with an extraordinarily dense structure is presented by DenseNet201, an architecture of Convolutional Neural Networks (CNNs). One defining feature of this design is the interconnectedness of its layers; in this setup, each layer takes data directly from every layer below it. By utilizing this concept, DenseNet201 can enhance the representation at each layer by reusing features extracted at each level of the architecture. The DenseNet201 method takes a comprehensive approach to extracting and understanding the visual features that differentiate fresh meat from spoiled meat when it comes to classifying the two. Because DenseNet201's convolution process can both capture local information and maintain close relationships between each part of the image, the model can detect subtle differences in meat quality. Also, the DenseNet201 architecture's dense blocks make it easy for data to flow strongly between layers, which improves the model's ability to grasp nuanced and complicated pictures. The architecture's pooling process is crucial to keep the accuracy of the representation of the meat image intact while reducing the dimensions of the extracted features.

While training, DenseNet201 optimizes its parameters and internal weights using the backpropagation technique, which involves iteratively adjusting the model depending on the difference between the actual labels and the predictions. This gives the model an excellent opportunity to study the visual cues that indicate when meat is fresh or has gone wrong. Using the training dataset as a basis, DenseNet201 achieved impressive accuracy in meat image classification, showing that it grasps the subtle visual differences between the two meat varieties. Metrics like recall, accuracy, precision, and F1 score are used to assess the DenseNet201 method's performance. By going through this test, we can

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learn how well the model distinguishes between images of fresh and spoiled meat. After comparing DenseNet201 to other models like VGG19 and learning about its strengths and weaknesses in the context of meat quality detection, this evaluation paints a clear picture of the model's potential for future development in this area.

When combining data at each layer, the DenseNet201 method takes a different tack than traditional architecture. Overcoming issues like "vanishing gradient" and "feature reuse," DenseNet201 allows for a direct and richer flow of information from one layer to the next by providing solid connections between its layers. Because of this benefit, DenseNet201 can discern between fresh and spoiled meat by efficiently understanding the relationships between each part of a meat image and capturing both global and local information. An additional benefit of a dense structure is that it allows the model to extract better features that are relevant to the visual distinctions between the two cuts of meat. Improving DenseNet201's ability to represent meat images in training requires tweaking the model's parameters and weights. This model can distinguish between visually fresh and spoiled meat with the correct dataset. As a result, the model's ability to differentiate between different types of meat is assessed using metrics like recall, accuracy, precision, and F1 score during the evaluation phase. The results of this evaluation shed light on how well DenseNet201 performs in meat quality detection and allow us to compare its performance to that of other models, like VGG19, in comparable classification tasks. Throughout, DenseNet201 demonstrated its remarkable visual discrimination between fresh and spoiled meat, laying the groundwork for future automated meat quality detection systems. The dense structure and feature extraction capabilities of DenseNet201 make it an attractive candidate for use in future, more advanced meat quality detection systems.

RESULT

Experiments utilizing the VGG19 and DenseNet201 models on an Acer Nitro 5 laptop with 32 GB RAM, a Core i9 processor, and an Nvidia RTX 3060 GPU demonstrated that the two models could be executed with adequate performance using these specifications. With 32 GB of RAM, it is feasible to load and process substantial volumes of data without encountering bottlenecks during intensive computing. The numerous cores of the potent Core i9 processor enable it to perform parallel computing tasks efficiently, thereby accelerating the training and inference phases of models. The Nvidia RTX 3060 GPU, renowned for its formidable similar computing capabilities, significantly enhances the execution of deep learning tasks that necessitate extensive matrix operations. Especially for models with quite deep and complex structures, such as VGG19 and DenseNet201, GPU computing speed accelerates the process of training and testing the model.

The selection of the Python 3.10 programming language additionally facilitates the implementation of these two models, given Python's widespread adoption as a language for experimentation and development in the domains of machine learning and deep learning. By leveraging libraries and frameworks like TensorFlow and PyTorch, the Python programming language facilitates the straightforward and effective implementation of models like VGG19 and DenseNet201. By integrating a robust GPU, a potent processor, ample RAM, and ideal programming language support, a laptop with these attributes establishes an environment that is exceptionally well-suited for conducting deep learning experiments with enhanced efficiency and timesaving.

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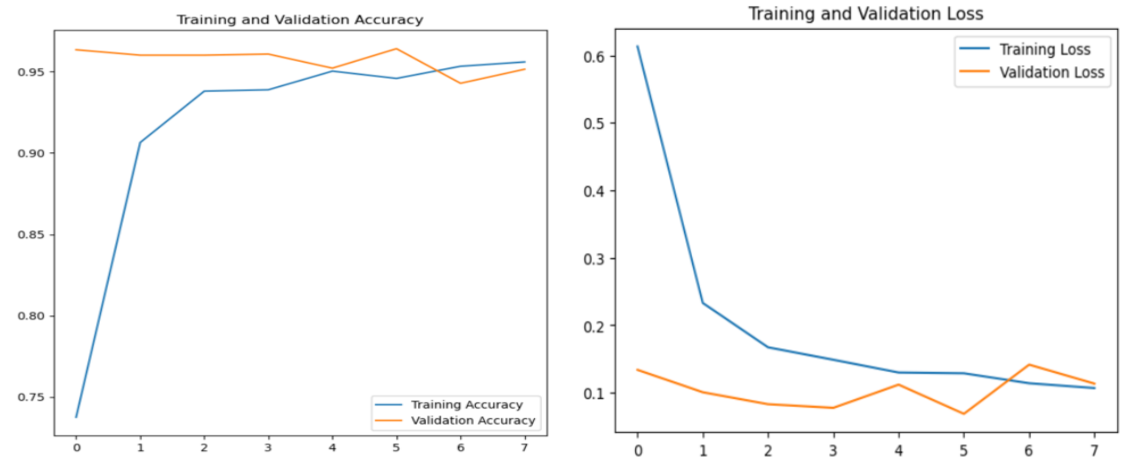

Figure 3. Performance accuracy training and loss VGG19
Source: Property researcher

Figure 3, following training, the VGG19 model exhibits a highly commendable performance on the Meat dataset, achieving an accuracy of 95.60% and a loss value of 0.1070. This magnitude of accuracy demonstrates the model's capability to accurately classify data in the Meat dataset with an exceptionally high degree of precision, that the model can reliably differentiate between and identify the classes within the dataset. While training, the model effectively reduced prediction errors, as indicated by the low loss value. This suggests that the VGG19 model exhibits a high degree of adaptability towards intricate patterns present in meat data. It is suitable for practical implementations where it can accurately classify diverse forms of comparable data with dependable predictions. Based on the substantial success rates and minimal loss values observed, it can be deduced that the VGG19 model exhibits considerable capability in extrapolating patterns from the Meat dataset. Moreover, it demonstrates promise as a dependable solution for classification tasks that demand exceptional precision.

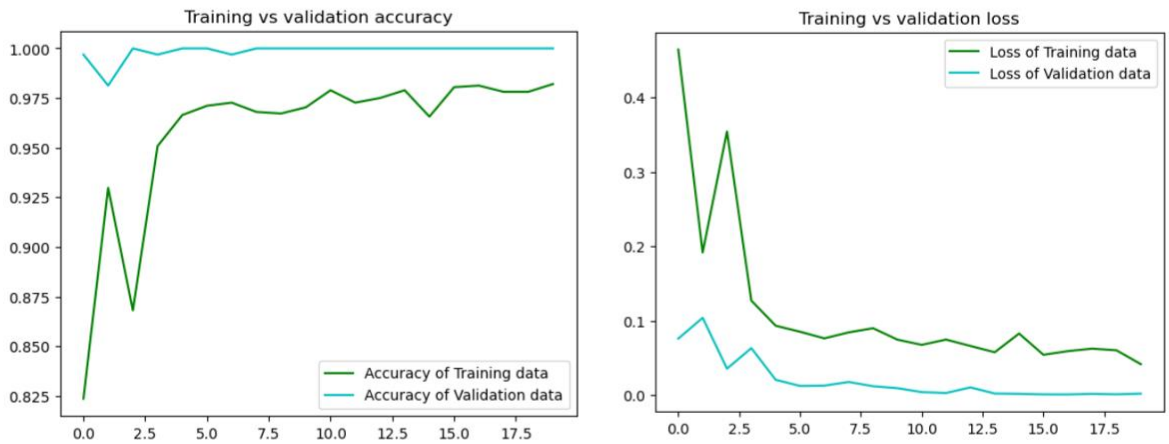

Figure 4. Performance accuracy training and loss Dense201
Source: Property researcher

Figure 4, with a loss value of 0.0418 and an accuracy level of 98.20%, the DenseNet201 model's training results are truly remarkable. The capacity of the model to correctly categorize data from the dataset utilized—here, potentially a more complicated dataset—is demonstrated by an exceptionally high degree of accuracy. The DenseNet201 model has shown its ability to identify and differentiate intricate features within the dataset accurately. A deficient loss value indicates that the model was trained effectively to reduce prediction errors. These outcomes demonstrate that DenseNet201 can change its internal representation to fit complicated data structures, which enables it to detect complex patterns

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accurately. When applied to classification problems requiring a high degree of accuracy, the DenseNet201 model reliably achieves an almost perfect level of precision with a low loss value. This model has proven to be an effective and dependable solution for medical image recognition and other real-world applications that demand detailed data classification, thanks to its outstanding performance on the datasets used.

According to the data, DenseNet201 routinely outperforms VGG19 in terms of accuracy. Achieving 98.20% accuracy was achieved by DenseNet201, while VGG19 only managed 95.60%. As a result of this disparity, DenseNet201 is clearly the better data classification model; it outperforms VGG19 on this dataset in terms of learning complex features and making accurate predictions.

Table 1. Dense210 accuracy, Precision, recall, F1-score reach 100%
Source: Property researcher

	Precision	Recall	F1-score	Support
0	1.00	1.00	1.00	1.00
1	1.00	1.00	1.00	1.00
accuracy	1.00	1.00	1.00	1.00
macro avg	1.00	1.00	1.00	1.00
weighted avg	1.00	1.00	1.00	1.00

All four-evaluation metrics—accuracy, precision, recall, and F1 value—reached 100%, indicating that the DenseNet210 model performed exceptionally well (Table 1). This proves that the DenseNet210 model achieves error-free data classification. When the accuracy and precision levels are both set to 100%, it means that the model is entirely accurate in all its predictions and that no false positives have occurred. The model was able to detect all positive instances without missing any, as indicated by the recall reaching 100%. The model has found the sweet spot between recall and precision when the F1 value is 100%. While further evaluation of the possibility of overfitting is necessary to guarantee its reliability in the broader range of testing situations, these results stating perfect performance demonstrate that the DenseNet210 model has very high generalization capabilities and is exceptionally capable of understanding the patterns present in the data.

DISCUSSIONS

The objective of the research is to assess the discriminatory capability of two models, Dense201 and VGG19, with respect to visual images presented alongside fresh and non-fresh meat. The primary objective is to evaluate the precision with which these two models distinguish the quality of meat exhibited in the provided image. Furthermore, this research aims to ascertain whether a notable disparity in performance exists between Dense201 and VGG19 with respect to this specific detection endeavor. The following are questions for research:

The degree to which these two models can accurately distinguish between fresh and non-fresh meat according to the provided visual images?

The primary objective of this study is to assess the efficacy of Dense201 and VGG19, two artificial neural network models, in discerning fresh and non-fresh meat using the provided visual images. Evaluating the precision of both models is central to this context, as it is intended to ascertain their effectiveness in discerning the quality of meat from a provided image. The implementation of visual meat quality detection holds significant ramifications within the food industry, as it guarantees food safety and satisfies consumer expectations regarding quality. Both the Dense201 and VGG19 models possess distinct advantages when it comes to the analysis of visual images. Dense201 is renowned for its capability of discerning intricate patterns within datasets, whereas VGG19 is frequently praised for its aptitude in acquiring more general image features. Nonetheless, when it comes to detecting fresh meat, a thorough evaluation of the performance of both methods is necessary. In this context, distinguishing fresh from non-fresh meat using visual imagery presents a significant obstacle. Meat

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quality, which is assessed by examining characteristics including color, texture, and cleanliness, is a critical determinant in this regard.

Compared to DenseNet201's 98.20% accuracy, VGG19's 95.60% is significantly lower. This study's image dataset suggests that DenseNet201 performs better than other methods when it comes to distinguishing between fresh and non-fresh meat. This data reveals that compared to VGG19, the artificial neural network design DenseNet201 may be more capable of feature extraction and recognizing the distinctions between fresh and non-fresh meat in this setting. It's encouraging to see that both have respectable accuracy, though DenseNet201, with its superior performance, might be the better pick for tasks calling for pinpoint precision.

In this study, the evaluation method comprised the application of a comprehensive dataset encompassing a vast array of fresh meats exhibiting substantial visual variations. F1-scores, recall, accuracy, and precision were utilized to assess the ability of both models to distinguish between new and non-fresh meat. Manually validated data will serve as a benchmark against which the classification accuracy of the two models will be evaluated. Regarding the detection of fresh meat, it is anticipated that the outcomes of this study will offer comprehensive insight into the benefits and drawbacks of each model. The analysis will primarily concentrate on the capability of Dense201 and VGG19 to distinguish meat quality, with an emphasis on the potential for substantial disparities. Furthermore, the results obtained from this study may serve as a foundation for the advancement of additional models that aim to enhance the precision of image-based fresh meat detection. This study will help the food industry choose the best model for meat quality detection by assessing both models' reliability.

Is there a substantial performance disparity between Dense201 and VGG19 regarding this detection task?

Assessing the performance gap between Dense201 and VGG19 in distinguishing between fresh and non-fresh meat using visual images is crucial for comprehending the capabilities and limitations of these neural network models. The purpose of this comparison is to identify notable disparities in their capacity to classify the quality of the meat depicted in the provided images. Assessing the quality of meat using only visual indicators is a significant obstacle, as subtle variations in color, texture, and other optical characteristics are crucial factors. Both Dense201 and VGG19 possess distinct architectural designs and exhibit specific capabilities in the domain of image recognition tasks. Dense201 is renowned for its highly interconnected layers, enabling it to capture intricate patterns in data effectively. On the other hand, VGG19 is acknowledged for its capacity to acquire more universal image characteristics. Nevertheless, accurately determining the freshness of meat necessitates a meticulous assessment of the effectiveness of both methods.

The evaluation methodology utilized an extensive dataset encompassing diverse categories of both fresh and non-fresh meat, each exhibiting substantial visual diversity. The performance of both models in distinguishing fresh meat from non-fresh meat based on the visual information displayed in the image was analyzed. Data will undergo manual verification and reorganization, ultimately serving as a benchmark for assessing the accuracy of model classification. The main objective of the analysis was to determine whether there was a significant difference in performance between Dense201 (Saputra et al., 2023) and VGG19 in fresh meat detection. The identification of a substantial discrepancy in their capacity to distinguish between fresh and non-fresh meat would be a crucial discovery. Comprehending the subtle distinctions in the capabilities and constraints of each model in discerning the quality of meat through visual indicators is essential for an industry that depends on precise evaluations of quality. The findings obtained from this research not only offer a deep understanding of the relative performance of these two neural network models but also provide fundamental knowledge for future model enhancement. Enhancing the precision of meat quality assessment through visual analysis has the potential to significantly influence the food industry by guaranteeing the delivery of secure and superior meat products to consumers. The main goal of this comparison is to provide helpful information for selecting the best model to improve the reliability and accuracy of meat quality detection systems.

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CONCLUSION

On the Meat dataset, the VGG19 model performed admirably, with a loss value of 0.1070 and an accuracy of 95.60%. It was suitable for real-world applications and showed adaptability to complex patterns in meat data. With an impressive loss value of 0.0418 and an accuracy of 98.20%, the DenseNet201 model proved to be very effective. By successfully identifying and differentiating complex features within the dataset, it proved that it could adapt its internal representation to fit intricate data structures. In terms of accuracy, DenseNet210 achieved 98.20%, while VGG19 only reached 95.60%. All four-evaluation metrics were at 100%, and the model successfully classified data without any errors. At a 100% F1 value, the model achieved optimal recall and precision. The DenseNet210 model can recognize patterns in the data and has good generalizability.

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