

Review on Machine Learning and Deep Learning and Its Benefit for Beef and Pork Classification

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Abstract

Machine learning and deep learning has been widely applied in wide application. Notably, deep learning recently received considerable attention in classification. This paper reviewed the theory regarding machine learning and deep learning and then concentrate the review on previous research that used the deep learning and machine learning technique for classification between beef and pork. It also reviewed the hybrid method to enhanced the accuracy.

1. Introduction

Meat stands as a staple in human diets, offering a rich source of protein vital for cognitive and physical well-being. With its widespread consumption, the market is abundant with various meat types. Although categorized for sale, some traders capitalize on soaring beef prices, yielding significant profits with minimal investment. Amidst these practices, there is an unfortunate occurrence of meat adulteration [1]. Consumer choices in meat purchases often hinge on factors such as safety, quality, and popularity, encompassing considerations like color, tenderness, flavor, and aroma [2]. Trust plays a pivotal role in shaping consumer preferences and behaviors, particularly when it comes to food choices and consumption habits [3]. Referencing Fig 1, the visual depiction highlights the contrasting textures between beef and pork.

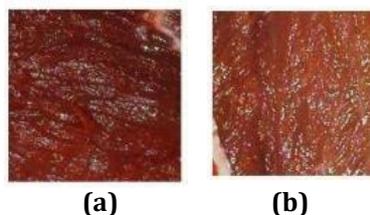


Fig. 1 Texture difference, (a) Beef; (b) Pork [1]

The pervasive influence of technological progress on daily life significantly enhances individuals' efficiency in executing various tasks. Technology catalyzes more effective and time-efficient task completion [4]. A prime example of this impact is evident in the livestock and food sectors, where technology can aid the public in discerning between natural beef and pork meat [5][6]. Given the challenge of distinguishing between the different textures of beef and pork, a digital approach is one of the alternatives to solve this problem. One such technological

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solution involves leveraging the power of Deep Learning, a rapidly advancing branch of Machine Learning, with Convolutional Neural Networks (CNN) at its forefront. Various architectural models, including LeNet, AlexNet, VGGNet, ResNet, EfficientNet, ResNet50, and DenseNet, exemplify the diversity within CNNs. Typically, these architectures consist of stacked convolutional layers, a pooling layer, and a fully connected layer. This technological integration holds promise for revolutionizing the identification and differentiation of meat types, addressing the challenges posed by subtle textural variations [7].

This work which successfully classified benign and malignant breast cancer histopathology imaging subtypes using a hybrid CNN- LSTM-based transfer learning approach. The dataset included 2480 clear images and 5429 cancer images. The previous research achieved an outstanding 99% accuracy in the binary classification of benign and malignant cancer [8]. This success inspires our exploration of a similar hybrid model approach to differentiate between beef and pork meat in our current study.

This review focus on related work from previous research based on theory regarding machine learning and deep learning and then concentrate the review on previous research that used the deep learning and machine learning technique for classification between beef and pork

2. Related Work

Food stands as a fundamental human necessity, demanding meticulous attention to both its quality and quantity. Plants and animals serve as substantial sources of nutrition for human consumption, with animals being a primary contributor [9]. The consumption of meat, whether per capita or overall, is expected to increase with the growing human population and rising incomes, further driving the demand for meat substitutes. Given that meat demand is intricately linked to socioeconomic, economic, and cultural factors [10], it becomes imperative to investigate how these variables influence consumer perspectives on livestock farming and meat consumption across different regions of the country [11].

Worldwide, meat consumption is on the ascent, driven by urbanization and growing per capita incomes. This surge in consumption surpasses previous records in numerous countries, alongside the increased availability and intake of alternative proteins. Despite its popularity, meat remains a contentious dietary choice, with tradition, cultural influence, and sensory and nutritional advantages encouraging its consumption. Simultaneously, concerns about human health, environmental impact, and animal welfare are also escalating.

2.1 Beef and Pork Meat

Beef holds a prominent position in global food consumption, and the Food and Agriculture Organization (FAO) anticipates its continued significance as a vital protein source, with substantial demand projected until 2050 [12]. In Indonesia, a predominantly Muslim country, and in Malaysia, where approximately 61% of the population follows Islam alongside other religions [4], there is a notable surge in the demand for beef during specific periods such as Ramadan and Eid al-Fitr. This observation is based on the Indonesian Central Office of Statistics and the Malaysia USCIRF (The US Commission on International Religious Freedom). This demand-supply imbalance, coupled with the economic value of beef [4], opens up possibilities for deceptive practices, where certain traders might blend pork. This deceptive practice poses a significant challenge, particularly for Muslim consumers, as pork consumption is prohibited in Islam. To address this issue, various methods, including physical examination (texture and color), sensory evaluation (tenderness, scent, and taste), chemical analysis (compounds), and microbiological assessments, can be employed. Pork and beef have unique smells that can be used to tell them apart [13] [14], [15]. Fig 2 shows the beef and pork image.

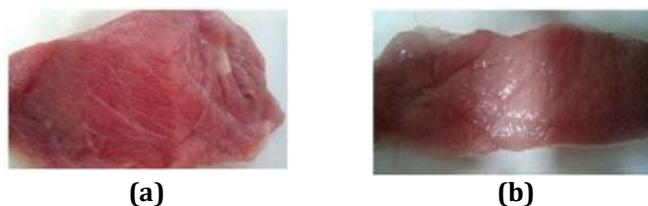


Fig. 2 Image (a) Beef; and (b) Pork [16]

Beef provides 207 calories, 18.8 grams of protein, 0 grams of carbohydrates, and 14 grams of fat per serving. It also contains essential minerals such as 11 milligrams of calcium, 170 milligrams of phosphorus, and 3 milligrams of iron. Additionally, beef offers 30 IU of vitamin A, 0.08 milligrams of vitamin B1, and novitamin C [17]. On the other hand, pork is rich in protein and provides essential nutrients such as potassium, phosphorus,

and zinc. Pork also contains niacin (vitamin B3), thiamine (vitamin B1), folate, riboflavin (vitamin B2), and vitamin B6 [18].

Pork is a widely consumed meat, both globally and in Australia. In Australian stores, fresh pork accounts for approximately 9% of all fresh meat, fish, and poultry sales. The Australian pork industry is experiencing growth due to increased domestic meat consumption and international demand. Despite this success, the industry faces ongoing challenges from strong competition abroad, emphasizing the need to enhance competitiveness and resilience. The continuous delivery of high-quality, fresh pork aligned with consumer preferences is crucial for supporting the growth of the Australian pig sector [19].

2.2 Texture, Marbling, Color, and Shape of Beef and Pork

Fresh beef offers a range of minerals, including protein, zinc, vitamin B6, B12, and others. In Indonesia, the distribution process of beef, as well as other types of meat, involves various stages, starting from slaughter and concluding at the marketplace for consumers. Throughout this distribution process, there may be a prolonged period, leading to the meat experiencing drip loss. This loss, which is rich in nutrients like protein, vitamins, and minerals, can affect the overall quality of the meat. Consequently, higher drip loss is associated with lower meat quality [20]. When selecting beef for optimal quality, certain criteria are employed. Firstly, the amount of collagen in the meat influences its tenderness, and healthy meat typically exhibits a resilient texture when pressed with a finger and the beef is more robust than that of pork, which is tender and easily stretched. We can truly feel the differences between the two when we handle them differently. Pork is quite chewy in texture. Stretching the meat is challenging since it feels firm and hard [19][20]. Secondly, the fat composition, known as marbling, acts as a wrapper for muscle tissue, preserving the meat's integrity when cooked and influencing its flavor. Lastly, the color of the meat varies based on the animal's genetics and age [7]. Secondly, the fat composition, known as marbling, acts as a wrapper for muscle tissue, preserving the meat's integrity when cooked, and influencing its flavor and the variation in fat is noticeable at the level of its flexibility. Cow fat is more formed and stiff than pork fat, which is more elastic in texture. Furthermore, pork fat is extremely moist and challenging to separate from the meat, whereas fat meat is slightly dry and has a fibrous appearance. But we have to exercise caution since hog fat can resemble cow fat in some places of the body, such as the kidneys. the color of the meat varies based on the animal's genetics and age, and Pork is lighter in color than beef and looks similar to chicken. However, this difference is often hidden by adding cow blood to pork, making it hard to tell them apart. Some parts of pork also look like beef, which makes it even more difficult to distinguish between the two. Lastly, Beef and pork cuts have different forms. Beef cuts like steaks and roasts are usually bigger, thicker, and have strong bones. Pork cuts, such as chops and tenderloins, are smaller, thinner, and have lighter bones. Pork has a thicker layer of external fat and a finer muscle structure with smaller fibers, while beef is darker red and has coarser fibers. Pork is lighter in color, similar to chicken. Despite these differences, some cuts can look similar, making them hard to tell apart by just looking [21].

Beef and pork stand out as popular choices in Asian countries, particularly Indonesia and Malaysia, where the demand for these meats continues to grow annually. Unscrupulous meat sellers take advantage of the rising cost of beef by blending it with pork, given its lower price. Numerous reports have surfaced regarding the fraudulent mixing of beef and pork. Buyers often rely on visual cues to differentiate between the two types of meat. Despite various methods for distinguishing meat, manual testing can lead to errors due to the limitations of human vision and the subjective nature of the testers [21]. Therefore, the deep learning method will be explored to classify between beef and pork.

2.3 Machine Learning

Machine learning, a subset of artificial intelligence (AI), is a technology branch designed to enhance processes by utilizing intelligent systems to analyze pre-recorded sample data. This advancement allows computers to recognize patterns and make decisions autonomously, eliminating the need for humans to explicitly define entire procedures. The machine learning process involves training, where a model is exposed to classified training data with various factors, enabling the system to recognize and process patterns effectively. Machine learning aims to simulate human pattern recognition objectively, enabling computers to learn tasks similarly to human learning when provided with extensive data and a suitable algorithm for analysis. The intersection of artificial intelligence, neural networks, and deep learning often complements machine learning, creating a comprehensive approach. Artificial intelligence is a broader field focused on computationally understanding intelligent actions and developing artifacts that exhibit such behavior, while machine learning specifically concentrates on how computers can learn from vast datasets. This integration stems from the convergence of statistics and computer science [22]. There are three types of machine learning which are supervised learning, unsupervised learning, and reinforcement learning as shown in Fig 3. The next section will introduce it briefly [23].

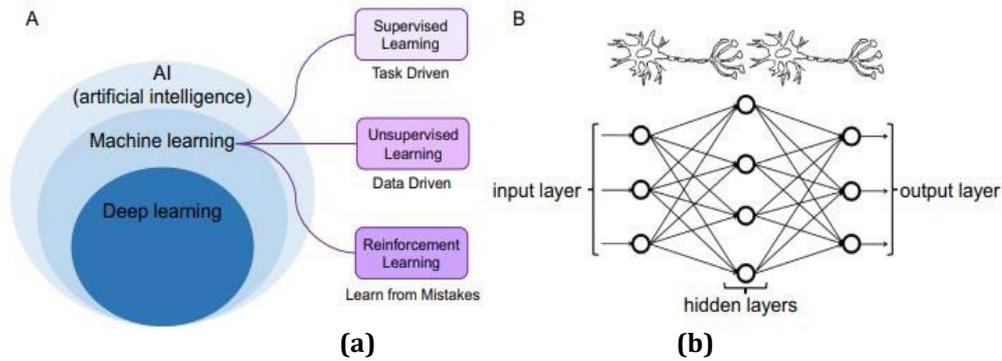


Fig. 3 (a) Hierarchy of AI; (b) Scheme of neural network [23]

2.3.1 Supervise Learning

Supervised learning is a learning approach where the training data is pre-labeled, facilitating pattern extraction. The suggested classification is denoted by the labels or classes present in the dataset [24].

2.3.2 Unsupervised Learning

Unsupervised learning is a part of the learning method where the dataset is the subject of the training for the pattern extraction process, and the data lacks classes and labels. In this approach, the data is initially processed by a computer to identify and extract patterns, which can be achieved through attribute extraction or by leveraging the inherent structure of the data.

2.3.3 Reinforcement Learning

Reinforcement learning is a learning method in which the computer is provided with positive or negative values based on its actions. If the computer performs well, it receives a reward, and if it performs poorly, it incurs a punishment. This encourages the computer to learn continuously and autonomously [25], [26].

2.4 Deep Learning

Deep learning is an algorithm that facilitates complex learning and analysis by utilizing deep neural networks with multiple layers. It has become a standard neural network, allowing computers to automatically define patterns without human description. While simpler methods are still used for basic systems with few input variables, deep learning excels in handling complex information, making it widely adopted in various aspects of social life, particularly in fields like medicine where feature extraction can be challenging [27].

Deep learning is an artificial neural network that incorporates weights at synapses and multiple layers. It excels in unveiling previously undiscovered connections or intricate patterns between inputs and outputs. Its key advantage lies in its ability to transform data from non-linearly separable to linearly separable through a sequence of transformations, facilitated by hidden layers. Deep learning can determine a non-linear decision boundary and model non-linear interactions between features, resulting in a non-linear modification of input until it reaches the output. The training process involves backpropagation [19],[28]. Fig. 4 illustrates the learning process with four layers.

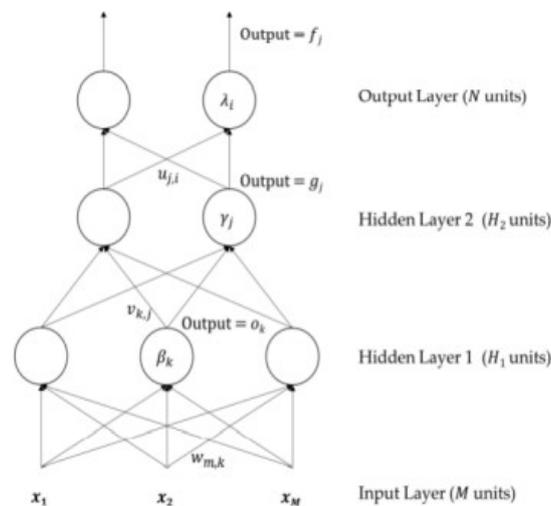


Fig. 4 Deep learning with four layers [29]

2.4.1 Neural Network

A neural network, also termed an artificial neural network, is a network of interconnected natural or artificial neurons designed to process information using mathematical or computational models based on a connectionism approach to computing. The concept of artificial neurons was first proposed by Warren McCulloch, a neurophysiologist, in 1943, aiming to create a mathematical description of information processing in biological systems. The initial neural network architecture consisted solely of input and output layers, now recognized as a single-layer network. The addition of a hidden layer to a single-layer network transforms it into a multi-layer network, comprising an input layer, hidden layer, and output layer, as depicted in Fig. 5 [30],[27].

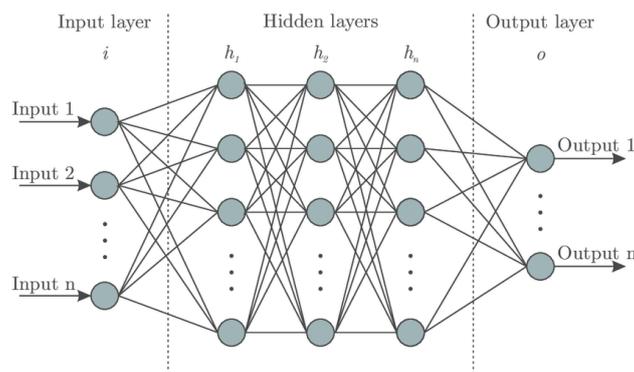


Fig. 5 Multi-layer network [28]

2.4.2 Activation Function

An activation function is a function that determines whether or not a neuron should be activated by adding a bias to the total of the weights. The activation function's objective is to introduce nonlinearity into neuron output. Several activation functions, particularly for binary classification, are frequently employed for classification issues [31].

2.5 Convolution Neural Network

Convolutional Neural Networks (CNN) belong to the category of Multilayer Perceptrons (MLP) designed to process two-dimensional input. CNNs have significant depth in their network architecture, earning them the classification of Deep Neural Networks. Notably, neurons in CNNs differ in size compared to MLPs. In MLPs, each neuron is one-dimensional, whereas in CNNs, each neuron is two-dimensional. CNNs employ convolution operations as part of linear operations [32]. The weights in CNNs are four-dimensional, as depicted in Fig. 6.

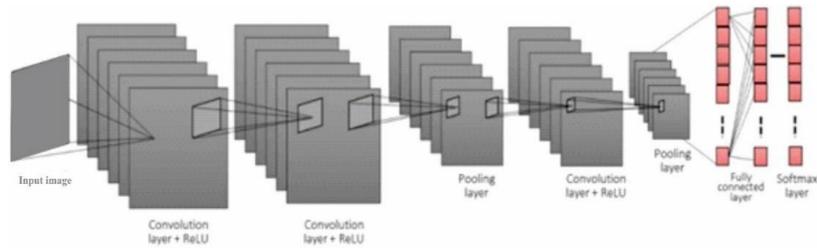


Fig. 6 The scheme of the CNN architecture model [33]

2.5.1 Convolution Layer

The cornerstone of the CNN is the convolutional layer, tasked with executing the convolution operation on the output of the preceding layer. Convolution, in this context, involves iteratively applying one function to the output of another function as shown in Fig. 7.

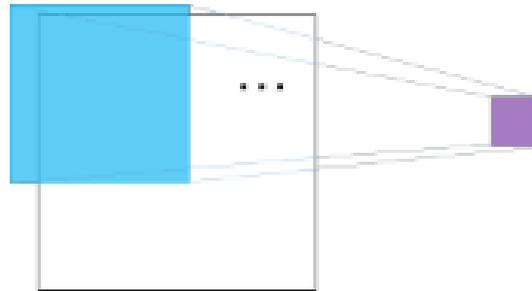


Fig. 7 Convolution process in CNN [34]

As depicted in Figure 7, the convolution employs blue kernels across the entire image at various offsets. The image subjected to convolution is the complete blue box. The kernel moves from the upper-left corner to the middle and right corner. Consequently, the convolution results are visible in the image on the right. Before training begins, three hyperparameters that determine the size of the output volume in the convolutional layer must be configured, including:

2.5.1.1 Number of Filter

The depth of the output is affected by the amount of filters used. Three separate filters, for example, will yield three different feature maps, resulting in a depth of three.

2.5.1.2 Stride

kernel's stride is the number of pixels it moves over the input matrix. A higher stride value yields a lower output. Stride values of two or higher are uncommon in convolution layers.

2.5.1.3 Zero Padding

When the filter does not fit the input image, zero padding is normally utilized. It sets to zero all members outside the input matrix, resulting in a larger or equal-sized output. Padding comes in three varieties:

- Valid padding: This is also referred to as no padding. If the dimensions are not aligned, the final convolution is dropped.
- The same padding: This padding ensures that the output layer and the input layer are the same size.
- Complete padding: By adding zeros to the input borders, this type of padding increases the output size.

CNN uses a Rectified Linear Unit (ReLU) adjustment to the feature map after each convolution operation, introducing nonlinearity to the model.

2.5.1.4 Pooling layer

Pooling layers provide a method for down-sampling feature maps by summing the presence of features in feature map patches [34]. The result of applying pooling layers and constructing a down-sampled or pooled feature map is a summary version of the features observed in the input. This is useful because slight changes in the location of features in the input detected by the convolution layer will result in the feature map being pooled with features in the same area. This capacity added by pooling is known as model invariance to local translation. There are two typical pooling methods: average pooling and max pooling, which summarize the average feature presence and the presence of the most active feature.

2.5.1.5 Average Pooling

Average pooling calculates the average value for each patch on the feature map. The following example of average pooling can be seen in Fig. 8 [34].

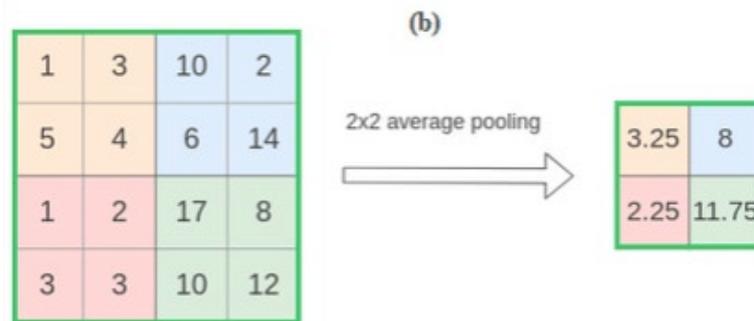


Fig. 8 Average pooling operation [34]

2.5.1.6 Max Pooling

Subsampling is the process of reducing the size of a data picture to enhance feature position invariance. In CNN, the subsampling method utilized is max pooling. In the illustration of Figure 2.8, max pooling divides the output from the convolution layer into multiple small grids, and then it selects the maximum value from each grid to construct the matrix-reduced image. The grids are colored red, green, yellow, and blue, representing the areas from which the maximum value will be chosen. Even when the image object undergoes a shift, the system's goal is to achieve consistent characteristics. The merging layer of the convolutional neural network (CNN) reduces the size of the image, making it easier to replace with a convolution layer and any necessary pooling layers later on. Fig. 9 illustrates the max pooling operation [34], [35].

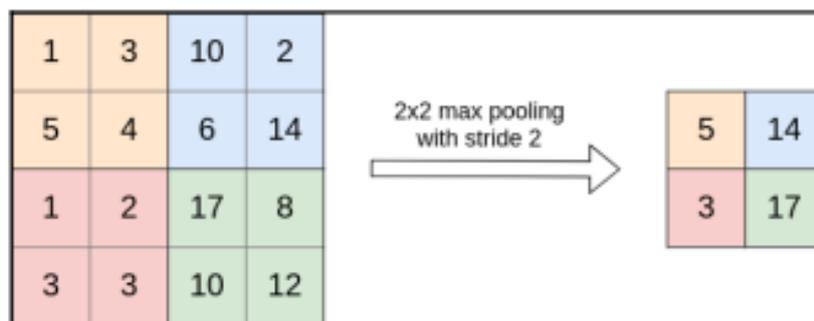


Fig. 9 Illustration of max pooling operation [34]

2.5.1.7 Dropout

Dropout layers are a very specific function in neural networks. Since normally a neural network comes with a large number of parameters, hence the problem of over-fitting might be one of the serious issues. So, the dropout technique is to randomly deactivate (disconnect) or activate (connect) of the neurons during the training being executed. Nowadays, this method has become one of the important parts of deep learning as it improves the speed of the model training and reduces the over-fitting problem efficiently. Below is the mathematical expression of the dropout function in 2.6 where the dropout in layer l is represented as [36]:

$$H^{(l)} = r^{(l)} * h^{(l)} \tag{2.1}$$

- $h^{(l)}$, is the original output of the layer l.
- $H^{(l)}$, is the new output of the layer l with dropout.

2.5.1.8 Fully-Connected Layer

Fully connected layers in a neural network are characterized by the connection of all inputs from one layer to each activation unit in the subsequent layer. In most popular machine learning models, the final layers are fully connected, consolidating the information gathered by preceding layers to produce the ultimate output. An instance of a fully connected layer is illustrated in Figure 2.4's hidden layer.

2.6 Resnet-50 Architecture

Figure 2.9 illustrates a ResNet-50 (residual neural network) with 50 layers of deep learning that was trained on at least a million photos from the ImageNet database. Most ResNet models utilize double or triple-layer skipping through nonlinearities (ReLU) and batch normalization. HighwayNet, a network that uses an additional weight matrix to obtain skip weights, is often employed. The ResNet-50 architecture consists of convolution block sequencing through average pooling. Softmax is used as the final classification layer, as depicted in Fig. 2.9.

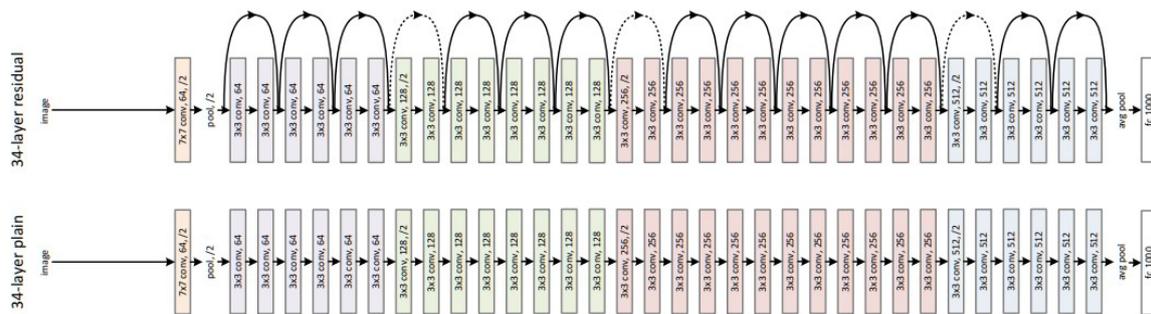


Fig. 10 The basic architecture of Resnet-50 [37]

ResNet-50 consists of five convolutional layers: conv1, conv2_x, conv3_x, conv4_x, and conv5_x. In the initial step, after loading the input image, it undergoes processing in a convolutional layer with 64 filters and a kernel size of 7x 7 (conv1 layer), followed by a max-pooling layer with a stride length of 2. Subsequently, the layers in conv2_x are paired based on how residual networks were related, as indicated in equation 2.14, showing two layers with kernel_size = 3x 3 and num_filters = 64 and 256, respectively. Another layer with kernel_size = 3x 3 and num_filters = 64 is duplicated three times, corresponding to the layers among pool, 2. This pattern continues similarly up to the fifth convolutional layer. The average pooling is performed at the fully connected layer, followed by softmax for classification. Table.1 shows the comparison of the convolution neural network's application with other related works.

Table 1 Comparison of convolution neural network's application with other related works

No	Author and Year	Item / Sample Tested	Method	Research Result
1	Salsabila, et al. (2021)[38]	Beef and Pork	CNN	- It is known that the highest accuracy of 97.56%
2	Junayed, M.S. (2019) [39]	classes of Acne	CNN	- This model has achieved an approximate accuracy of as much as 99.44% for one class and the rest were also above 94% with fairly high precision and recall scores.
3	Yadav, S., (2021)[40]	Food image (cup-cake, red velvet cake)	CNN	- Achieve quite a good accuracy of 77.20%. - proposed VGG-16 has achieved significant improvement in accuracy up to 85.07%
4	Lee J. M., et al. (2022)[41]	Beef	CNN	- It provided high confidence over 75% for these cuts.
5	Inik O., et al. (2018)[42]	Animals images	CNN	- The classification of the animals was realized with 91.2% accuracy with VggNet and 67.65% with AlexNet.
6	Attokaren D. J., et al (2017)[43]	Food	CNN	- An accuracy of 86.97% for the classes

This section discusses the outcomes of prior research that can serve as a point of reference for the current research topic. The selection of previous research aligns with the challenges addressed in this study, specifically the limitations of manual techniques in visually and olfactorily differentiating between beef and pork. Given the need for technological solutions, several studies have explored the application of image processing and deep learning for the accurate distinction between beef and pork.

2.7 Support Vector Machine (SVM)

SVM is a relatively recent supervised machine learning algorithm that emerged in the 1990s. It is a supervised ML using linear and non-linear datasets, which may be used for regression and classification issues. SVM seeks to determine the best hyperplane between two classes in a given dataset [44]. A hyperplane is a line that divides two groups of data. The hyperplane margin, which is the distance between the closest data between two separate classes and the maximum point, better known as the support vector, can be used to discover a hyperplane. Fig. 11 shows an illustration of a support vector machine.

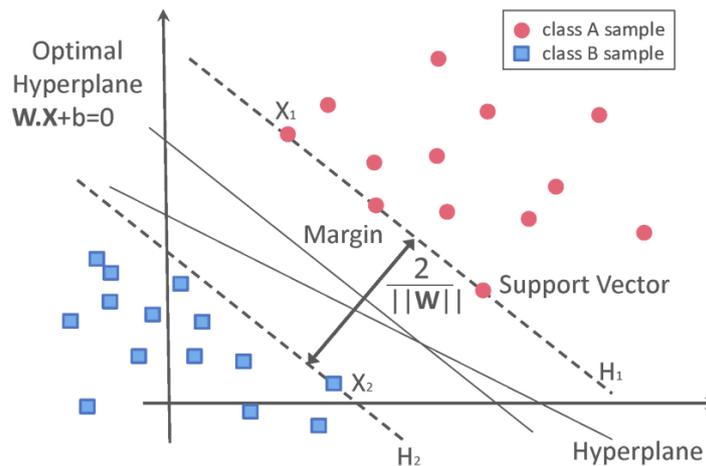


Fig. 11 SVM training with two classes of samples [45]

In Figure 2.7 the line between the dotted lines is a hyperplane, with the support vector, namely the green and blue points on the dotted line and $\frac{2}{\|W\|}$ as the hyperplane's margin. The SVM linear classification hyperplane is denoted as follows:

$$f(w, x) = w \cdot x + b \tag{2.2}$$

The SVM classifier is utilized in this study in the very last stage of the fully connected layer of CNN to boost elasticity and efficiently suit a date length to flip the kernel [46].

Table 2 The use of support vector machine in the classification of various objects

No	Author and Year	Item / Sample Tested	Method	Research Result
1	Farinda et al., (2018) [47]	Beef Images	SVM	- The highest accuracy was 97% for cold beef
2	Fengou L et al., (2021) [48]	Meat Adulteration	SVM	- Freshly ground meat, 96.67%
3	Neneng et al., (2020) [49]	Wood Type	SVM	- The accuracy was 91.3%
4	Sumari A.D.W et al., (2021) [50]	Coconut Meat Selection	SVM	- The accuracy was 50%
5	Neneng et a., (2016) [51]	Image Classification Type Meat	SVM	- The accuracy was 87.5%

2.7.1 Linear Kernel

Kernel is a function in SVM that is used to help solve difficulties involving data dimensions. It is also known as the kernel trick. The SVM technique employs a collection of mathematical functions known as kernels. The kernel function takes data as input and converts it to the desired form. The linear kernel is the most basic kernel function in SVM [52]. When the data being studied is already linearly segregated, linear kernels are utilized. Linear kernels

are appropriate when the data includes many characteristics, as transferring to a higher dimensional space does not significantly enhance speed. The linear kernel function has the following equation:

$$k(x, x') = x^T x' \quad 2.3$$

- $k(x, x')$: This is the kernel function, often denoted as k , which takes two input vectors, x , and x' , and computes a scalar value.
- x^T : This represents the transpose of the vector x . In the context of a linear kernel, x is often a feature vector.
- x' : This is another feature vector.

2.8 Convolutional Neural Network (CNN) ResNet-50 and Support Vector Machine (SVM)

The CNN-SVM hybrid model synergizes two powerful machine learning algorithms: Convolutional Neural Network CNN(ResNet50) and Support Vector Machine (SVM)[53][54]. CNN (ResNet50) is excellent in extracting biased information from raw pictures and learning globally persistent features [55]. The SVM classifier, on the other hand, is efficient at binary classification and efficiently decreases generalization errors on unknown information. The proposed CNN(ResNet50)-SVM hybrid model utilizes SVM as a binary classifier. In this setup, CNN(ResNet50) acts as a feature extractor, and SVM functions as the binary classifier [41]. The architecture of the hybrid CNN(ResNet50)-SVM model is formulated by integrating the outcome layers of the CNN(ResNet50) model with SVM classifiers, as illustrated in Fig. 12.

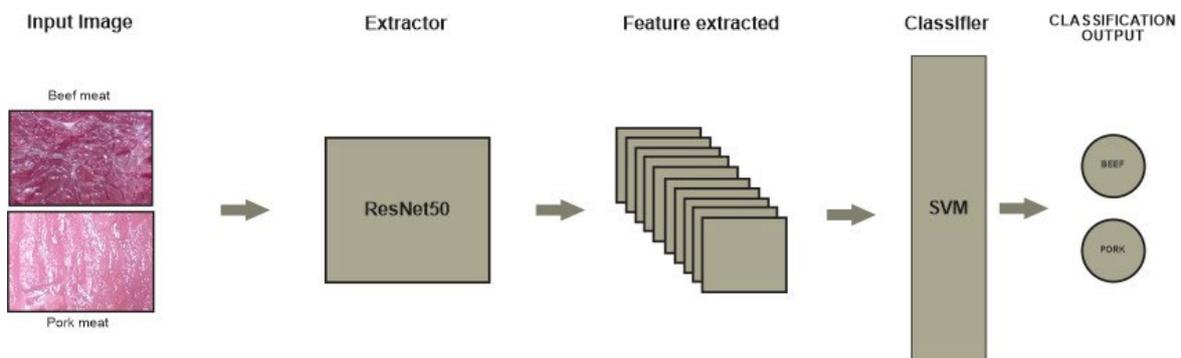


Fig. 12 Architecture of the proposed hybrid CNN-SVM model

During training, the SVM utilizes the feature extracted from the CNN(Resnet50)[37][56]. Once trained, the SVM classifier engages in the identification process, making new judgments on images based on the automatically derived features [44]. Table 3 provides a comparative overview of CNN and SVM with other relevant works. Notably, no existing research has integrated CNN-SVM for the differentiation of beef and pork, making this novel approach a focus of exploration in the current project.

Table 3 Comparison of CNN and SVM with other related works

No	Author and Year	Item/Sample Tested	Method	Research Result
1	Navaneeth B., et al (2018) [57]	Chronic Kidney Disease (CKD)	CNN-SVM	- Achieved an accuracy of 98.25%
2	Ren L., et al (2023) [58]	13 types of fish species	CNN-SVM	- Best classification accuracy of 98.2%
3	Xu Jinyang., et al (2022) [59]	Individual or group behavior of pigs	CNN-SVM	- 94.6368 % of accuracy
4	Karthik B.U., (2023)[53]	Tumor images	CNN-SVM	- Achieving classification accuracy around 98% and 98.5%.
5	Khairandish M.O et al (2022) [60]	MRI images	CNN-SVM	- Obtained as 98.49%.

Conclusion

In conclusion, based on the review, hybrid method between deep learning and machine learning shows improvement in differentiating between different type of meat. The basic theory regarding deep learning also presented in this paper to give basic knowledge to the reader who are new to this field.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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