Development of an Intelligent Meat Spoilage Detection and Grading System Using Particle Swarm Optimization-based Convolutional Neural Network

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Abstract: *This research developed an intelligent meat spoilage and quality grading system using a particle swarm optimization-based convolutional neural network. It addressed the problems associated with the subjective manual assessment of meat quality and inefficient and expensive meat quality grading systems as well as the lack of a comprehensive dataset for meat quality detection. This research created a new dataset for meat spoilage and quality detection. Furthermore, a PSO-based convolutional neural network was trained with the new dataset for the classification and the grading of the meat. The Python code is then integrated into the Raspberry Pi 4 to make it a stand-alone system. Comparative analysis indicated that the PSO-based CNN performed better compared to the baseline CNN by 2.91% for accuracy, 2.49% for precision, 0.99% for F1-score, 1.87% for recall, 2.74% for specificity and 1.14% for sensitivity. The obtained results implied improved food safety in the food processing industry and retail environments. In addition, the intelligent system provides support to human experts for accurate assessment of meat quality.*

Keywords: *Particle swarm optimization, Convolutional neural network, Meat quality, Grading system.*

Introduction

Animal flesh, commonly known as meat, serves as a dependable protein source. Its nutritional value is attributed to the provision of carbohydrates, proteins, fats, vitamins, and minerals, making it a significant dietary component [1]. Meat stands as one of the most widely consumed foods globally, with over half of the world's population incorporating it into their diets. Notably, China, the world's most populous nation, contributes to approximately one-third of global meat consumption and has played a crucial role in the consumption surge observed over the last two decades [2]. Worldwide, around one hundred and ninety million metric tons of red meat, including goat, beef, lamb veal and pork, are produced annually, with less than 25% of individuals in developed nations consuming half of this quantity. Beef, a common product found in supermarkets, is frequently purchased by customers. Fresh and high-quality beef is rich in nutrients, as emphasized by [5]. However, challenges such as increasing beef prices and potential market downturns lead some vendors to engage in fraudulent practices by selling spoiled meat. Consumers are advised not to consume beef that is no longer fresh and emits an unpleasant odour, as it may pose health risks. Meat spoilage is influenced by various factors, including contaminating bacteria and enzymes. Improper slicing and washing of fresh meat can expose it to bacterial infection, while inherent enzymes can contribute to nutrient breakdown, leading to spoilage [3]. Bacteria thriving on carbohydrates during metabolism produce gases such as volatile organic compounds (VOC), ammonia (NH_3), and hydrogen sulfide (H_2S) affecting the meat's colour and causing mucus formation. The quantity of microorganisms present impacts the rate of meat deterioration. With a potential hydrogen (Ph) value of 5.7 and a composition comprising approximately 75% water, 19% protein, 2.5% intramuscular fats, and 1.2% carbohydrates, beef is particularly susceptible to spoilage [6]. Beyond spoilage, contaminated meat can jeopardize consumer health by potentially carrying pathogenic bacteria that can cause foodborne illnesses and result in financial losses through increased damage and reduced meat shelf life [7]. To prevent spoilage, proper meat washing and storage practices are essential. National standardization agency of Indonesia (BSN) recommends storing meat in fresh, chilled, or frozen forms, with different temperature requirements for cooling or heating [7]. Heating meat at high temperatures sterilizes it against microbial contamination while cooling inhibits enzyme activity and microbial growth to prevent spoilage [9]. Computer vision, an artificial intelligence field rooted in image processing, machine learning, and pattern recognition, empowers computers to capture, process, analyze, comprehend, and make informed judgments based on digital images obtained from cameras [10]. Alongside, meat grading plays a vital role in ensuring the quality and safety of meat products for consumers. Grading is a systematic assessment that categorizes meat based on various attributes, such as marbling, colour, texture, and overall freshness [8]. The goal is to provide consumers with reliable information about the quality of the meat they purchase. Marbling, the distribution of intramuscular fat, is a key factor in grading beef, as it significantly impacts tenderness and flavour. United States of America Department of Agriculture (USDA), for instance, employs a grading system that includes categories like 'Prime', 'Choice', and 'Select', each reflecting different levels of marbling and overall quality [11]. Colour is another essential criterion, as fresh meat exhibits specific colour characteristics indicative of its condition. The grading process helps consumers make informed choices while also guiding pricing in the market. By adhering to standardized grading systems, the meat industry ensures transparency and builds trust with consumers, fostering a marketplace where quality is consistently maintained and communicated [13].

The lack of an automated and efficient system for meat spoilage detection as well as meat grading hampers food safety, causes delays in meat processing, incorrect or evaluation of meat food, and compromises consistent quality assessment. There is a need to design and implement an intelligent system that can accurately detect spoilage, grade meat based on predefined standards, and provide real-time monitoring to enhance efficiency and ensure food safety. Various food items, including meat, are prone to contamination by microorganisms. The availability of water and other nutrients creates an ideal breeding ground for the proliferation of these microorganisms [14]. Responding to the heightened demand and costs, there is a manipulation of beef sales wherein individuals participate in the exchange or sale of spoiled meat for fresh ones in marketplaces and other commercial settings [15]. Over an extended period, identifying significant levels of spoiled meat becomes a challenging task for consumers, making it unfit for consumption [16]. Furthermore, the existing limitations of prevalent deep learning methods stem from the absence of a standardized dataset for network training. This research endeavours to tackle these challenges by establishing comprehensive datasets for training purposes, incorporating recent deep learning approaches. The ultimate goal is to create an intelligent system for the detection of meat spoilage and grading.

Materials and methods

System hardware

The intelligent system for detecting meat spoilage and grading is comprised of several interconnected components. These components encompass a camera module, Raspberry Pi 4B, LCD, and power supply. The system is strategically designed with the Pi camera serving as an input device capturing images of the meat. Input data in the form of images is received by the Raspberry Pi, where it undergoes pre-processing, and due to its excellent representation ability, the convolutional neural network (CNN) model is employed to detect and categorize features [17]. The model is specifically trained to extract features and generate a feature map, subsequently deployed onto the Raspberry Pi board. Output devices include the LCD for displaying the result.

System block diagram

The Pi camera are input device; the Raspberry Pi 4 Model B is shown in Fig. 1. The block diagram of the units that comprise the intelligent meat detection system and the system flow diagram is presented in Fig. 2, respectively.

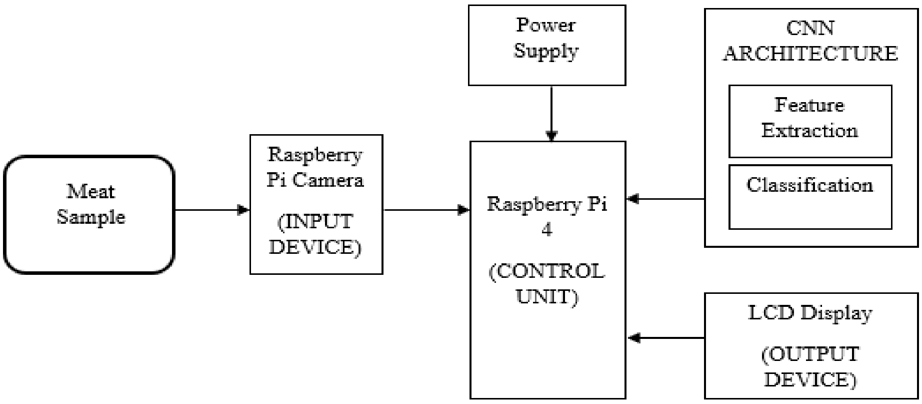

Fig. 1 System block diagram

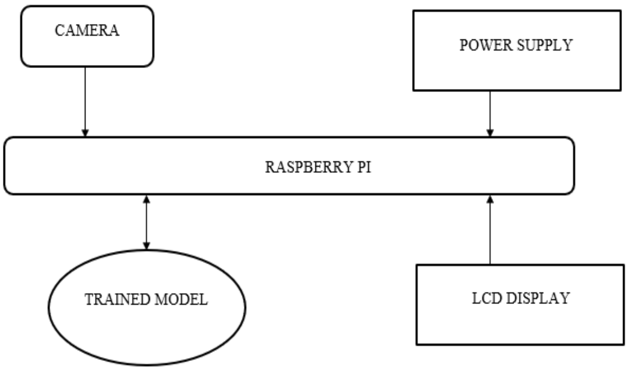

Fig. 2 Flow diagram of the intelligent meat spoilage detection and grading system

The system employed Raspberry Pi camera V2.1 for its high quality imaging capabilities, Raspberry Pi 4 Model B for its compact and fast computing features and LCD 2004 display for result visualization as depicted in Fig. 1. Two models including the CNN and particle swarm optimization-based CNN (PSO-CNN) were developed and trained with the varied images of meat samples as shown in Figs. 1 and 2. The models extract salient features needed to classify and grade the meat samples.

System flowchart

The operational sequence of the system is illustrated through a flow chart (Fig. 3). The camera is initiated at the system's outset capturing images of the meat. Subsequently, this data is fed into the CNN for classification. The outcome of the classification establishes the condition of the meat, distinguishing between fresh and spoiled. The system then further classifies the fresh meat into prime, choice and select. The system autonomously generates output based on the classified result.

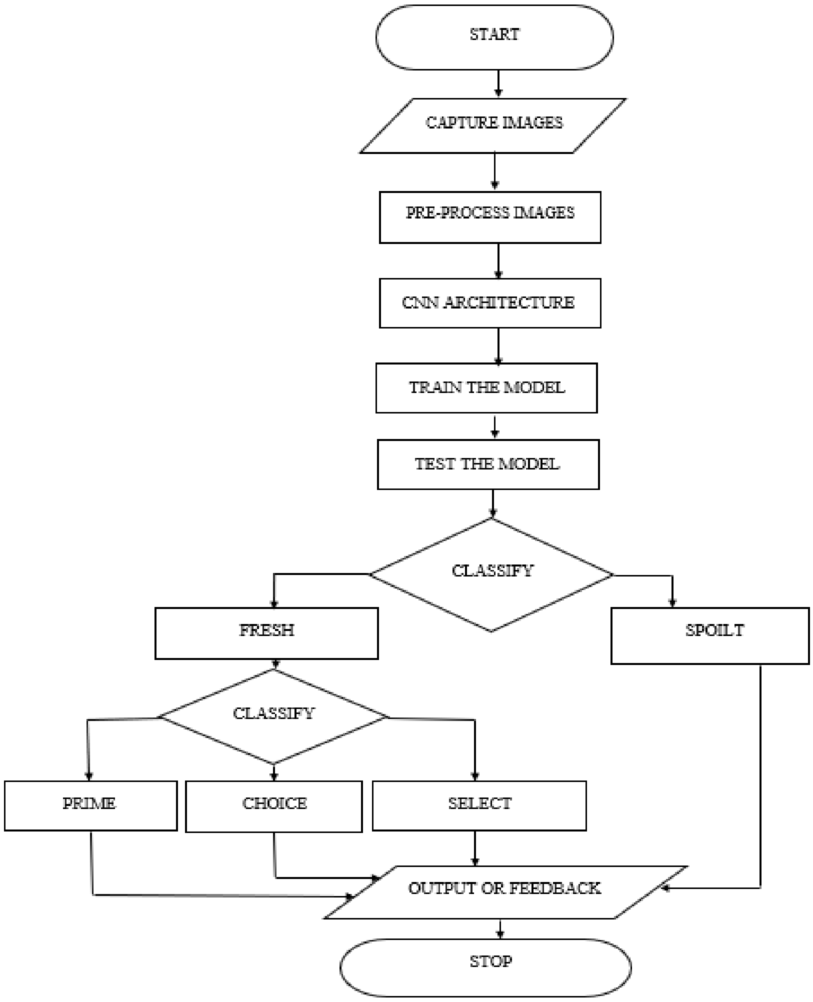

Fig. 3 System flowchart

Fig. 4 outlines the procedural steps involved in training and testing the model. Initially, the dataset is loaded and annotated for processing. The loaded dataset is then processed in a pipeline, involving conversion to CSV format for improved compatibility and subsequent transformation to record. Following this, the dataset undergoes reading and normalization by dividing it by 255. TensorFlow serves as the platform for training the model, which incorporates four distinct layers. The initial layer specifies the input shape as 256×256×3 RGB, while the output layer introduces the number of classes. The network is flattened, and a dense layer is incorporated with the sigmoid function as the activation function before defining the class [18]. The optimization process employs the Adam optimizer, initializing the loss function. The model undergoes training for 50 epochs to achieve desirable accuracy (Table 1).

After training, the model is saved and tested, introducing a new dataset for prediction.

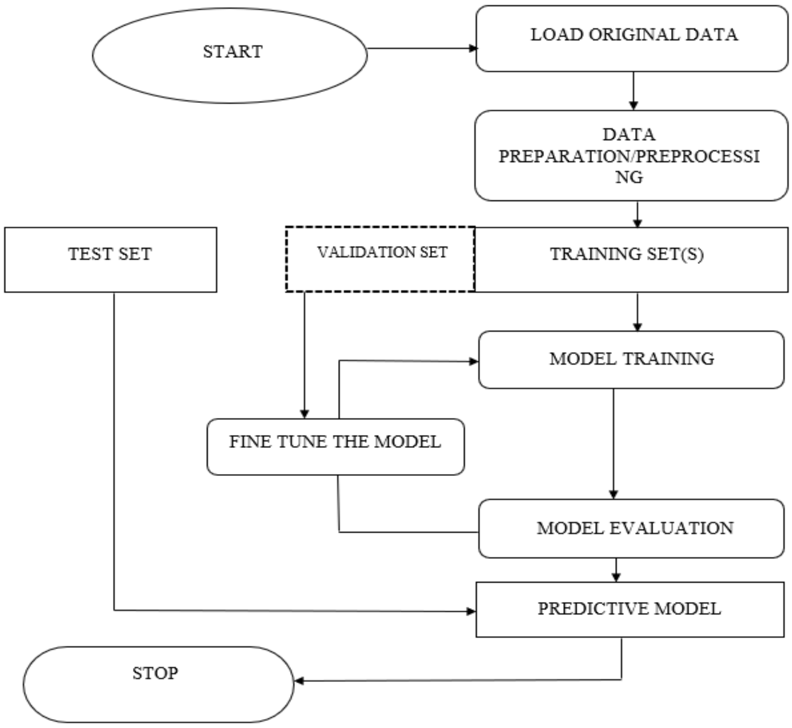

Fig. 4 Steps involved in training and testing the model

Table 1. Specification of CNN

S/N	Hyperparameter	Description of baseline CNN	Description of PSO-CNN
1	Batch-size	64	64
2	Loss function/optimizer	Adam optimizer	Adam optimizer
3	Epoch	50	50
4	Activation function	Sigmoid function (output layer)	Sigmoid function (output layer)
5	Network architecture	InceptionNet	InceptionNet
6	Learning rate	0.0001	0.001 (PSO-tuned)
7	Numbers of layers	32	47 (PSO-tuned)
8	Number of hidden nodes	128	64 (PSO-tuned)
9	Pooling layer	MaxPool	MaxPool

Dataset

The first objective of the project is to create a comprehensive data set of meat samples, including spoilage characteristics and corresponding grading attributes. Hence a total of 32 000 images were gathered in the data collection process. The data collected includes 25 000 images of fresh meat and 7 000 images of spoilt meat. The fresh meat images were further classified into 'prime', 'choice' and 'select' meat samples. 9 000 images were classified as 'prime', 9 000 images were classified as 'choice' and 8 000 images were classified as 'select'. The images were captured using a high-resolution camera. The data collection process involves Select, Prime, Choice and Spoilt classes as shown in Plate I (Fig. 5).

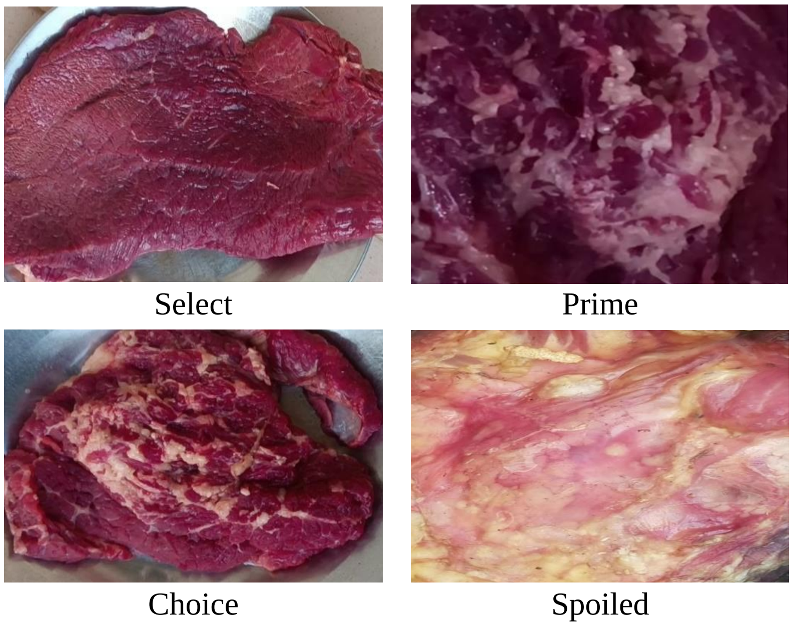

Fig. 5 Plate I: image classes

Image annotation

Computer Vision Annotation Tool (CVAT) stands out as a powerful open-source solution tailored to the intricate demands of computer vision annotation tasks. With its comprehensive capabilities, CVAT supports the annotation of various data types, including images, videos, and point clouds. One notable feature that sets CVAT apart is its flexibility, offering users the ability to define and annotate diverse visual elements within their datasets. What further enhances CVAT's utility is its capacity to be deployed on a local server. This decentralized approach grants users full control over their annotation environment, ensuring security and privacy while also providing the freedom to customize the tool to meet specific project requirements.

CVAT is an invaluable asset for annotating a dataset that encompasses a range of meat quality categories, including 'prime', 'select', 'choice', and 'spoilt'. The tool's intuitive interface and versatile annotation capabilities allowed for efficient and accurate labelling of diverse visual attributes within the dataset. The local server installation not only ensured a seamless annotation process but also provided a robust foundation for maintaining data integrity and security throughout the annotation workflow. CVAT's adaptability and user-friendly features made it a go-to tool for annotating complex visual data, contributing significantly to the success of this project. The annotation is shown in plate II (Fig. 6).

CNN architecture

Having acquired the dataset, the second objective of this research is to develop the computer vision system using the InceptionNet machine learning model for accurate identification of meat consumption conditions. The CNN recognized as a highly effective technique for image recognition scenarios, represents an advanced implementation of artificial neural networks [4, 12]. For this project, InceptionNet was used (Fig. 7). The InceptionNet has 14 blocks before it produces the output. In the first stage, the network starts with an image size of 256×256×3, then it goes through 1×1 convolution layer, and then through 3×3 MaxPool layer. In the second stage, it then goes through 1×1 convolution layer, then passes through 3×3 convolution layer followed by 3×3 MaxPool. Stage 3 consists of 2 inception blocks and MaxPool layer at the end. The inception blocks don't have the same channel allocation. Block 1 has 256 channels and

Block 2 has 480 channels. The image is then transformed again after going through the two inception blocks and the MaxPool layer. The final stages 4 and 5 are similar to the previous three stages. Stage 4 has five inception blocks and MaxPool layer. The first four blocks have 512 channels and the last block has 832 channels. Stage 5 has two inception blocks and GlobalAveragePool. The first block has 832 channels and the second block has 1024 channels.

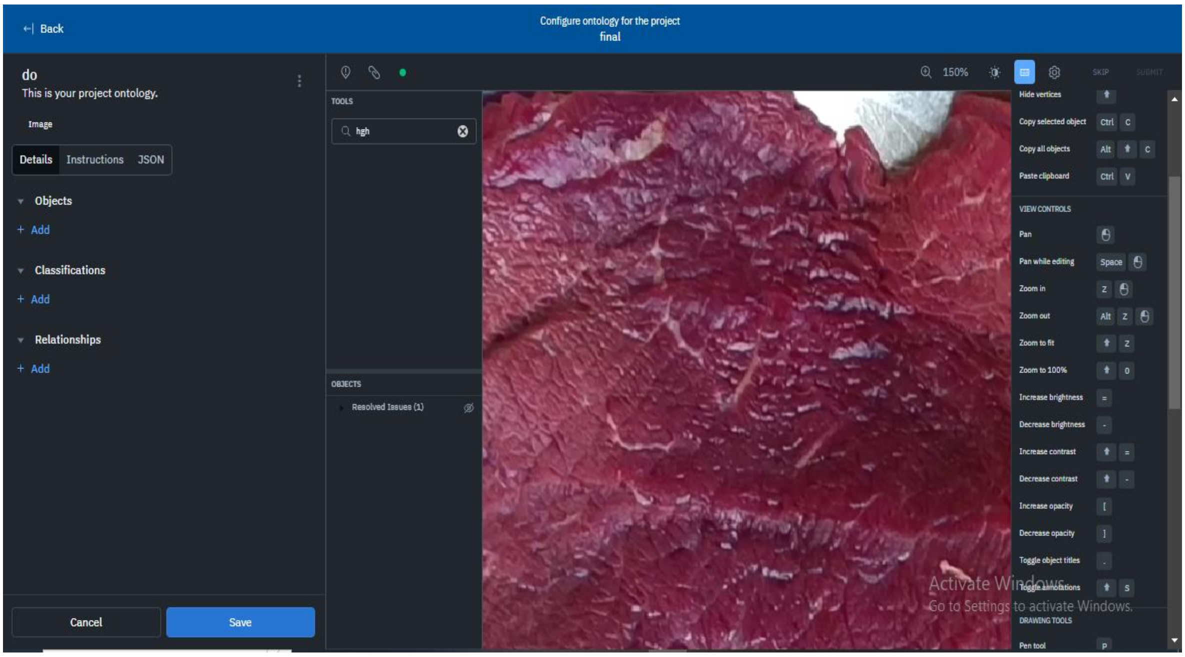

Fig. 6 Plate II: image annotation

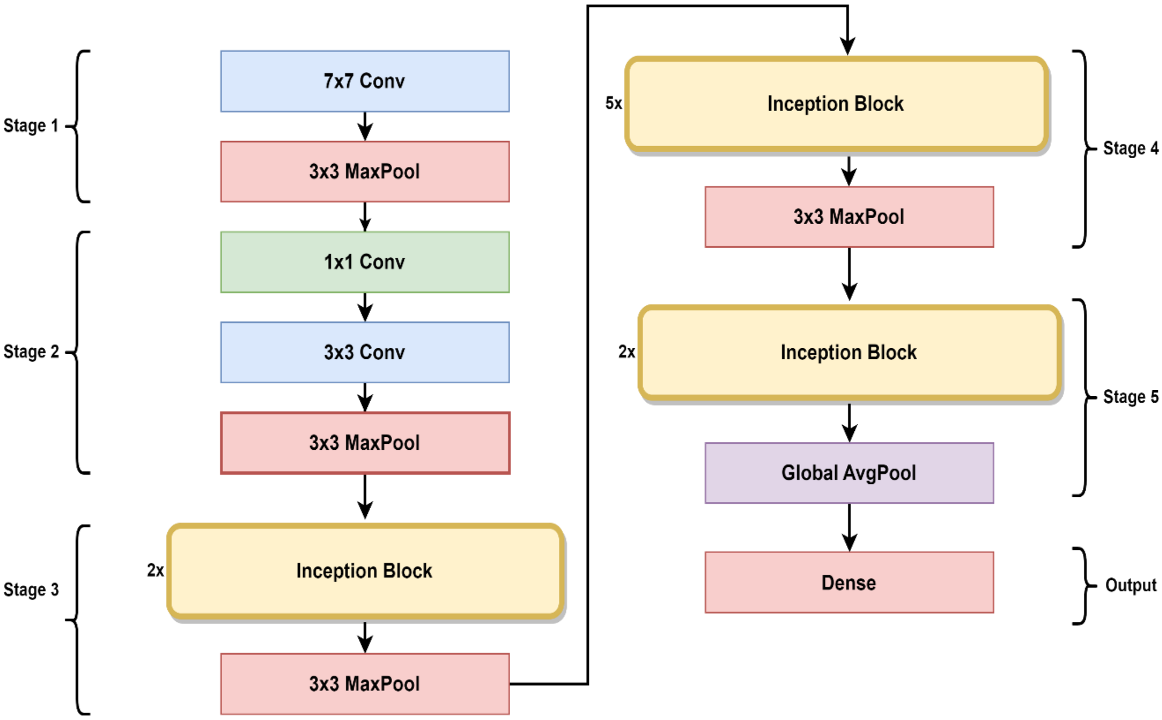

Fig. 7 CNN architecture

PSO-CNN

The PSO is used to optimize the InceptionNet hyperparameters by finding the optimal values of the learning rate ℓ, numbers of hidden layers $\mathcal{L}$ and number of hidden nodes Ƕ. This process can be represented mathematically as:

$$x_i = (\ell_{i,} \mathcal{L}_{i,} \text{Ƕ}_i), \tag{1}$$

where $\ell_{i,}$ is the learning rate of the InceptionNet; $\mathcal{L}_{i,}$ is the number of layers of InceptionNet; and Ƕ_i is the number of hidden nodes for the i-th particle.

The particle is evaluated by training the InceptionNet using the hyperparameters' optimal values and the performance is measured using the loss function.

The fitness function to be minimized is given as:

$$f(x_i) = -J(\ell_{i,} \mathcal{L}_{i,} \text{Ƕ}_i), \tag{2}$$

where J is the cross-entropy loss.

The InceptionNet hyperparameters are updated by PSO using the equation [19, 20]:

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}, \tag{3}$$

where $x_i^{(t)}$contains the parameters ℓ, $\mathcal{L}$, Ƕ; v is the velocity of the particle.

Thus, the mathematical relationship between the PSO and the InceptionNet is given as:

$$x_{opt} = arg\ {}^{min}_{x}\ \text{J}(\ell, \mathcal{L}, \text{Ƕ}), x = (\ell, \mathcal{L}, \text{Ƕ}), \tag{4}$$

where x_{opt} is the best hyperparameters found by the PSO.

This equation indicates that PSO finds the optimal parameter values for the InceptionNet. This afford the optimized InceptionNet the ability to perform optimally by extracting and learning the salient image features.

Fig. 8 shows the integration between the PSO and the InceptionNet architecture. The integration starts by initializing the PSO parameters and the inceptiontionNet hyperparameters to be optimized. Then, the position and velocity of the initialized particles are computed. This enables the computation of the fitness function through the minimization approach. Furthermore, the position and the velocity of the particles are updated and the best hyperparameters including the learning rate, number of hidden layers and number of hidden nodes are computed. The computed best hyperparameters are used to train the InspectionNet for optimal meat classification. This is expected to perform better than the traditional InspectionNet because the PSO possesses the ability to optimize the hyperparameter values for training the network rather than relying on random and non-optimal values of the hyperparameters.

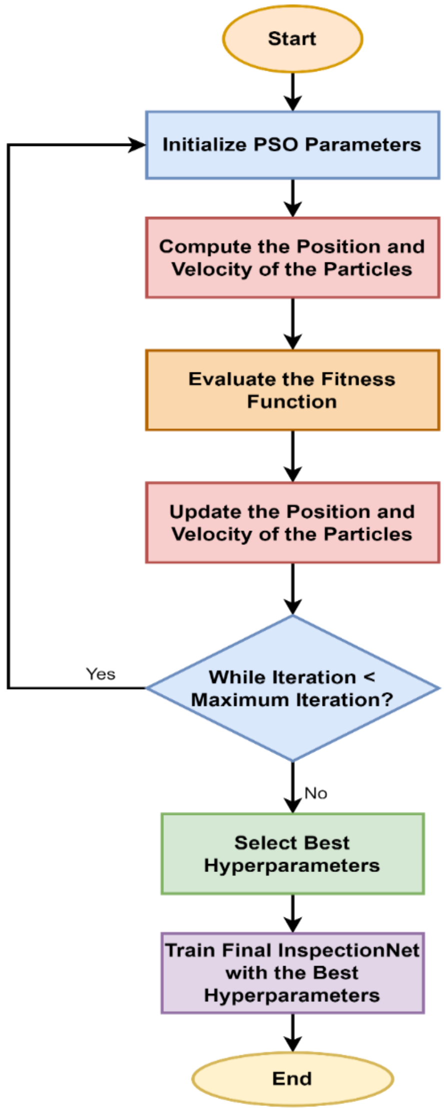

Fig. 8 PSO-CNN InceptionNet flowchart

Performance evaluation

Assessing the performance of machine learning algorithms stands as a pivotal facet of any practical project endeavour. It provides insights into the effectiveness of each algorithm, delineating those that yield satisfactory outcomes from those that do not. While accuracy is often employed as a gauge for model performance in classification algorithms, it's important to note that it's not the sole determinant of a model's quality. In this study, we utilized a range of evaluation metrics, including F1-score, precision, recall, confusion matrix, accuracy, and sensitivity. These metrics, widely recognized and employed, offer a comprehensive measure of performance and are visually represented in plots to depict the models' comparative performances.

Model performance evaluation

The intelligence mechanism on which this system relies is the PSO-CNN InceptionNet model. The integration of PSO-based InceptionNet for meat spoilage detection and grading in this research has yielded significant improvements over the conventional CNN approach, particularly the InceptionNet architecture. The PSO-based InceptionNet not only demonstrated enhanced accuracy but also exhibited a notable increase in the system's overall efficiency. By leveraging PSO for optimization, the model demonstrated superior convergence during training, increased sensitivity, and allowed for better weight adjustments and improved fine tuning of the neural network's parameters [21]. This optimization resulted in a more robust and adaptive model, which showcased superior performance in detecting subtle features and nuances associated with meat spoilage and grade. The utilization of PSO in the training process contributed to the network's ability to generalize well on diverse datasets, thereby enhancing its capability to accurately grade and classify meat spoilage across varying conditions. In comparison to the conventional CNN, the PSO-CNN approach has not only elevated the accuracy of our system but has also demonstrated the practical implications of incorporating optimization techniques in deep learning models for real-world applications, ultimately contributing to the reliability and efficacy of our meat spoilage detection and grading system. Hence, results obtained from the implemented system include the evaluation of system performance through the representation of accuracy, sensitivity, specificity, recall, precision, and F1-score.

The PSO-CNN model was trained for 50 epochs. The observed rising curve for accuracy and decreasing curve for loss over the training epochs in this project signifies the progressive learning and refinement of the model (Fig. 9). As the neural network undergoes successive iterations through the training dataset, the accuracy curve ascends, indicating an improvement in the model's ability to correctly classify instances. This ascent reflects the network's increasing proficiency in capturing and leveraging intricate patterns and features present in the data. Concurrently, the descending curve for loss illustrates a reduction in the disparity between the predicted and actual values, emphasizing the model's capacity to minimize errors over time. The convergence of these curves is indicative of the network's enhanced capability to generalize and make more accurate predictions, reflecting the iterative learning process as the model refines its internal representations of the input data, ultimately leading to a more effective and precise meat spoilage detection and grading system.

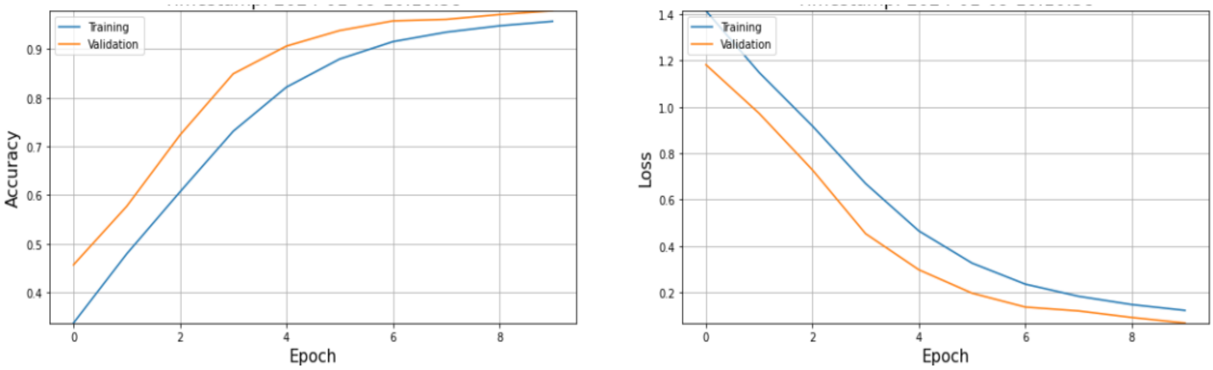

Fig. 9 Accuracy and loss plot over training epoch

The system performance comparison between the Convolutional Neural Network (CNN) utilizing Inception NET architecture and the PSO-CNN is presented in Table 2. In the accuracy measure, the PSO-CNN outperformed the conventional CNN, achieving an impressive accuracy rate of 98.42%, compared to 95.64% resulting in a performance improvement of 2.91%. The precision metric, which measures the accuracy of positive meat class predictions, also favoured the PSO-CNN with a precision of 96.67%, surpassing the conventional CNN's precision of 94.32% and resulting in 2.49% improvement. Likewise, the F1-score, a harmonic mean of precision and recall, demonstrated the superiority of PSO-CNN with a value of 96.17%, while the conventional CNN achieved a slightly lower F1-score of 95.23%, resulting in an enhancement of 0.99%. Additionally, the recall metric, which assesses the ability to capture true positive meat classes, also favoured the PSO-CNN with a recall of 94.91%, outperforming the conventional CNN's recall of 93.17% resulting in an improvement of about 1.87%.

Table 2. Metrics of evaluation

Evaluated metrics	**CNN (InceptionNet), %**	**PSO-CNN, %**	**Improvement, %**
Accuracy	95.64	98.42	2.91
Precision	94.32	96.67	2.49
F1-score	95.23	96.17	0.99
Recall	93.17	94.91	1.87
Specificity	93.38	95.94	2.74
Sensitivity	96.67	97.77	1.14

Also, the sensitivity and specificity metrics, which assess the sensitivity and specificity and provide insights into a model's ability to correctly identify positive and negative meat instances, respectively favoured the PSO-CNN with a specificity of 95.94%, and sensitivity of 97.77%, outperforming the conventional CNN's specificity of 93.38 percent and sensitivity of 96.67% resulting in an improvement of 2.74% for specificity and 1.14% for sensitivity respectively. These Individual performance metrics collectively highlight the enhanced capabilities of the PSO-CNN in achieving higher accuracy, sensitivity and precision, emphasizing its efficacy in the classification task compared to the standard CNN.

The performance comparison plot between the PSO-CNN and the ordinary CNN visually unveils compelling insights across various key metrics. In terms of accuracy, PSO-CNN consistently outperforms its conventional counterpart, showcasing a higher ability to correctly classify both positive and negative instances as seen in Fig. 10. Precision, recall, and F1-score metrics further emphasize the superior performance of the PSO-CNN, indicating its precision in positive predictions, sensitivity to actual positive instances, and a harmonious balance between precision and recall. Also, PSO-CNN model exhibits heightened sensitivity, crucial for capturing all relevant positive instances, while maintaining an elevated specificity, indicating a proficient ability to correctly identify negative instances. The comparative plot underscores the efficacy of integrating PSO for optimization, highlighting its positive impact on multiple performance metrics and reinforcing its role in enhancing the overall effectiveness of the meat spoilage detection and grading system.

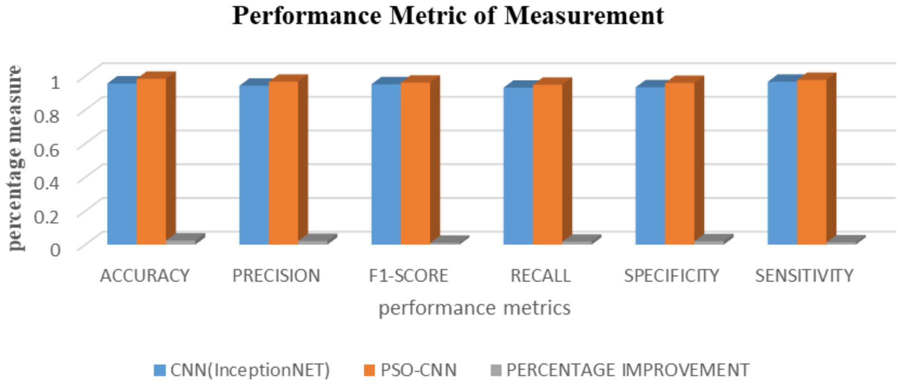

Fig. 10 Performance metrics visualization for CNN vs PSO-CNN

System performance evaluation

The recall of the system over training epochs provides a good insight into the system's ability to identify and capture all actual positive meat class instances. As the training progresses, the recall curve illustrates the model's improvement in minimizing false negatives class and effectively recognizing positive cases within the dataset. Table 3 shows the values for recall measure per progressing training epoch (up to the 15 epoch) of the both CNN and PSO-CNN. This was generated using the Keras on plugin train history function.

Table 3. Recall per training epoch

Epoch	Recall CNN, [%]	Recall PSO-CNN, [%]
1	37	45
2	39	41
3	41	50
4	43	54
5	45	58
6	47	60
7	47	61
8	49	63
9	51	60
10	90	94
11	93	95
12	94	95
13	93	96
14	91	95
15	93	97

Fig. 11 shows the graphical representation shown in Table 3 of recall over epoch. A rising recall curve signifies an enhanced capacity to correctly identify a higher proportion of positive instances, crucial for applications where missing actual positive cases is undesirable. This trend underscores the system's growing sensitivity to positive instances, contributing to the overall reliability of the meat spoilage detection and grading system. Monitoring recall over training epochs is particularly significant in scenarios where the cost of false negatives is high, as it ensures the model's effectiveness in minimizing the omission of true positive cases and, consequently, in enhancing the overall performance of the system.

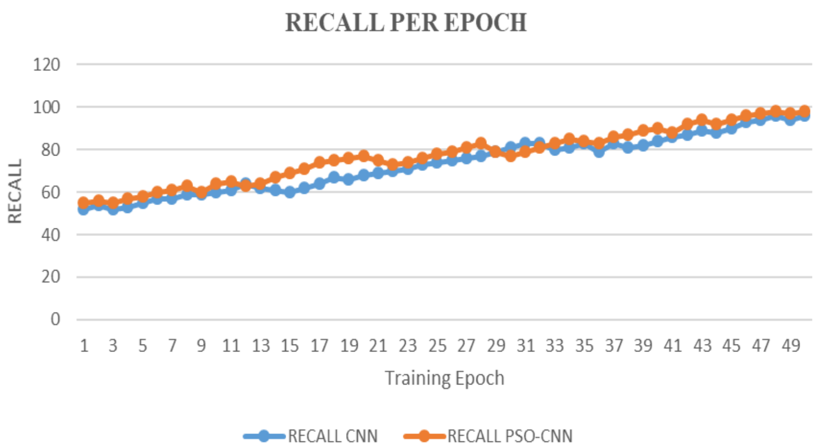

Fig. 11 Recall rate over training epochs for PSO-CNN

Table 4 shows the values for precision measure per progressing training epoch of the both CNN and PSO-CNN model.

Table 4. Precision per training epoch

Epoch	Precision CNN, [%]	Precision PSO-CNN, [%]
1	33	42
2	37	41
3	42	56
4	43	56
5	44	53
6	45	55
7	47	53
8	48	55
9	50	57
…	…	…
45	88	94
46	90	93
47	91	91
48	92	96
49	93	95
50	94	96

Fig. 12 shows the graphical representation shown in Table 4 of precision over epoch. The precision of the system reflects the evolution of its ability to make accurate positive predictions while minimizing false positives. As the training progresses, the precision curve provides valuable insights into the model’s capacity to maintain a high ratio of correctly predicted positive instances relative to the total instances predicted as positive. A rising precision curve signifies an improvement in the model’s capability to avoid misclassifying negative instances as positive. This trend is indicative of the system's growing proficiency in making precise and reliable predictions, contributing to the overall robustness of the system.

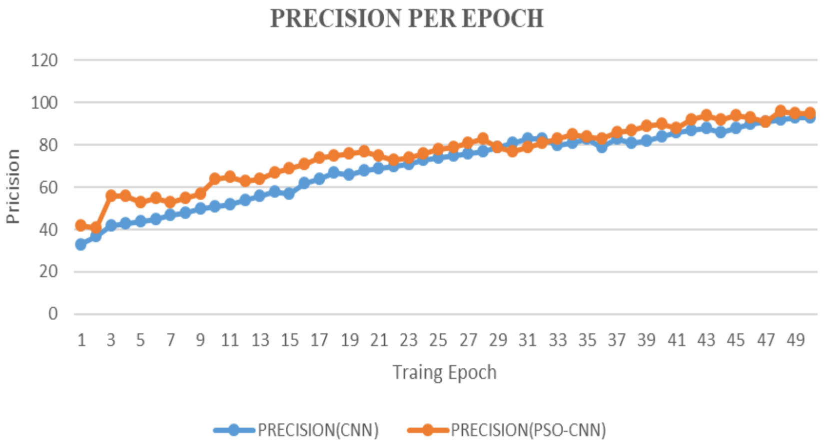

Fig. 12 Precision rate over training epochs for CNN vs PSO-CNN

Table 5 shows the values for sensitivity measure per progressing training epoch (up to the 15 epoch) of the both CNN and PSO-CNN models.

Table 5. Sensitivity per training epoch

Epoch	Sensitivity CNN, [%]	Sensitivity PSO-CNN, [%]
1	37	51
2	39	48
3	41	50
4	43	51
5	45	52
6	47	55
7	47	53
8	49	53
9	51	57
10	90	91
11	93	93
12	94	91
13	96	96
14	95	98
15	96	97

The sensitivity plot (Fig. 13), tracks the system's performance over training epochs by measuring its capability to correctly identify actual positive meat class instances. The sensitivity curve provides a dynamic representation of how well the model adapts to recognizing positive cases throughout the training process. A rising sensitivity curve indicates an improvement in the model's ability to minimize false negatives, effectively capturing a higher proportion of positive instances. This upward trend reflects the system's increasing sensitivity to the presence of meat spoilage, which is crucial in applications where missing actual positive cases is a significant concern. The monitoring of sensitivity over training epochs underscores the system's progressive refinement, ensuring it becomes increasingly adept at identifying and responding to the subtle features associated with meat spoilage and grade, ultimately enhancing the overall reliability of the system with the PSO-based model outperforming CNN.

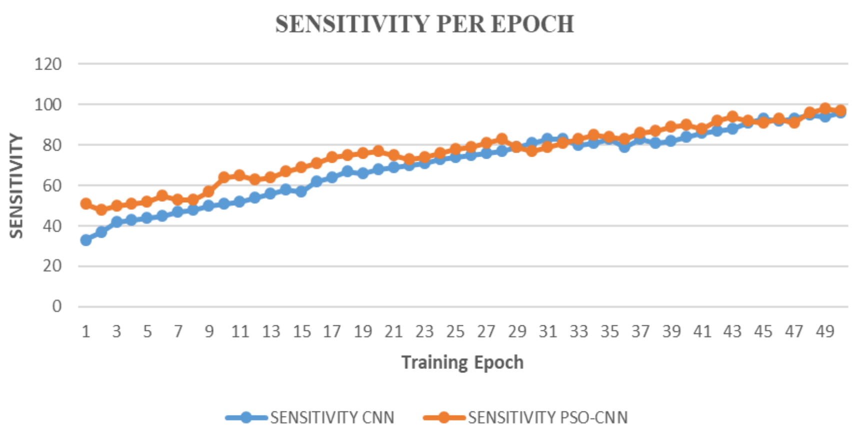

Fig. 13 Sensitivity rate over training epochs for PSO-CNN

Table 6 shows the values for accuracy measure per progressing training epoch of the both CNN and PSO-CNN.

Table 6. Accuracy per training epoch

Epoch	Accuracy CNN, [%]	Accuracy PSO-CNN, [%]
1	52	55
2	54	56
3	52	55
4	53	57
5	55	58
6	57	60
7	57	61
8	59	63
9	59	60
…	…	…
45	90	94
46	93	96
47	94	97
48	96	98
49	94	97
50	96	98

Fig. 14 shows the graphical representation shown in Table 6 of recall over epoch. The accuracy of the system over training epochs hints on the system overall performance in correctly classifying both positive and negative instances. As the training progresses, the accuracy curve depicts the model’s ability to make correct predictions across the entire dataset, considering both true positives and true negatives. A rising accuracy curve indicates an improvement in the model's generalization and proficiency in handling diverse instances, showcasing its overall effectiveness in meat spoilage detection and grading.

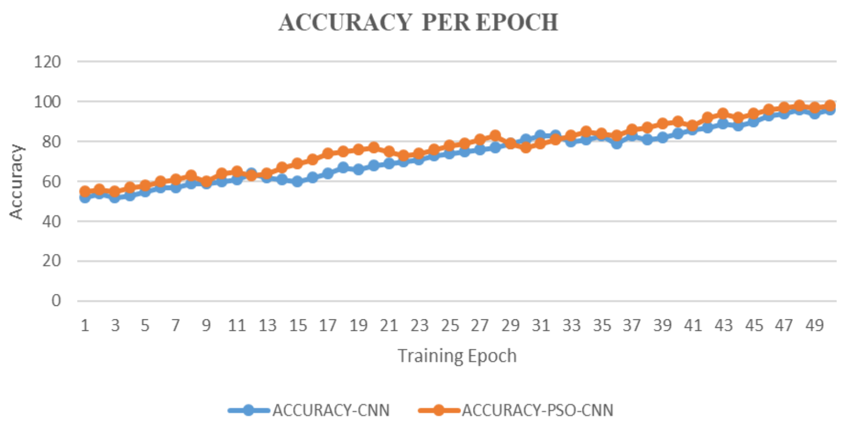

Fig. 14 Accuracy rate over training epochs for CNN vs PSO-CNN

Table 7 shows the values for F1-score measure per progressing training epoch of the both CNN and PSO-CNN.

Table 7. F1-score per training epoch

Epoch	F1-score CNN, [%]	F1-score PSO-CNN, [%]
1	35	44
2	36	41
3	37	47
4	39	54
5	42	58
6	44	60
7	43	61
8	41	63
9	50	60
…	…	…
45	90	94
46	93	95
47	94	95
48	95	96
49	94	94
50	95	96

Fig. 15 shows the graphical representation shown in Table 7 of F1-score over epoch. The F1-score of the system over training epochs encapsulates the harmonic balance between precision and recall, offering a holistic assessment of the model's performance. As the training progresses, F1-score curve reflects the model's ability to achieve a simultaneous optimization of both precision and recall. A rising F1-score curve indicates an improved equilibrium between correctly identifying positive instances and minimizing false positives and false negatives. The plot show how the system can be particularly valuable in scenarios where there is a need for a balanced approach to classification, as it ensures that the system maintains both high precision and high recall.

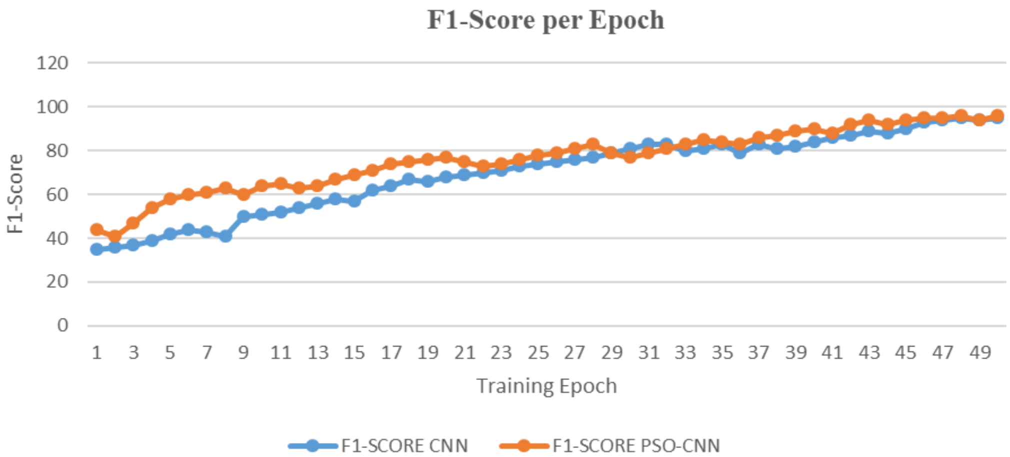

Fig. 15 F1-score over training epochs for CNN vs PSO-CNN

Table 8 shows values for specificity measure per progressing training epoch of the both CNN and PSO-CNN. This was generated by using the Keras on plugin train history function.

Table 8. Specificity per training epoch

Epoch	Specificity CNN, [%]	Specificity PSO-CNN, [%]
1	56	55
2	52	53
3	51	51
4	47	54
5	48	58
6	49	60
7	49	61
8	50	63
9	51	60
…	…	…
45	89	94
46	91	95
47	92	95
48	92	96
49	90	94
50	93	96

Fig. 16 shows the graphical representation shown in Table 8 of specificity over epoch. The specificity of the system provides a focused evaluation of its capability to accurately identify negative instances, emphasizing its proficiency in minimizing false positives. As the training progresses, the specificity curve demonstrates the model's improvement in correctly classifying true negatives while reducing instances of false positives with the PSO-based model, doing better.

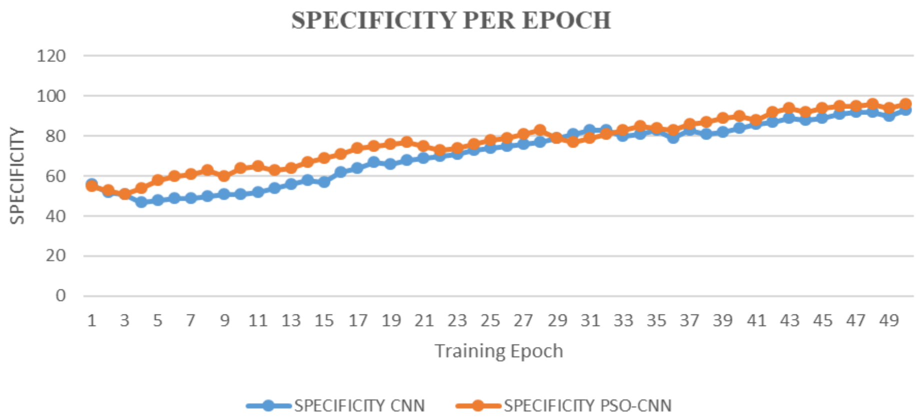

Fig. 16 Specificity over training epochs for CNN vs PSO-CNN

Software development

The algorithm implemented for classifying meat samples leveraged the power of Python programming language, with TensorFlow serving as the primary deep learning framework. TensorFlow is renowned for its flexibility and efficiency in building and training complex neural network models. The implementation also made extensive use of additional libraries such as pandas, which is invaluable for data manipulation and analysis. These libraries facilitated seamless handling and preprocessing of the meat sample dataset, ensuring optimal compatibility with the CNN architecture. Google Colaboratory, a free cloud-based platform, played a pivotal role in the development and execution of the algorithm. The platform provided an interactive and collaborative environment for running Python code, enabling easy sharing and real-time collaboration on the project. The cloud-based nature of Google Colaboratory eliminated the need for local setup and resource constraints, allowing for the utilization of high-performance computing resources.

Incorporating PSO into the algorithm added a layer of intelligence to enhance the CNN's performance. PSO, implemented through a dedicated library, facilitated the tuning of hyperparameters such as learning rate, number of layers, and number of hidden nodes. This optimization technique allowed the algorithm to dynamically adjust its configuration, maximizing the model's accuracy and robustness in classifying meat samples. The seamless integration of PSO into the algorithm underscored the commitment to achieving an optimal and efficient neural network design for meat sample classification.

Conclusion

These meat spoilage detection and grading system presented in this work demonstrates a holistic approach to addressing food safety concerns through the amalgamation of advanced machine learning techniques and efficient hardware design. The system's core functionality lies in its ability to classify meat samples based on spoilage, providing an early warning mechanism to mitigate potential health risks associated with consuming deteriorated products. The utilization of CNNs, specifically the InceptionNet architecture, highlights the significance of robust image recognition in detecting subtle visual cues indicative of spoilage.

The rationale behind the implementation of this system stems from the imperative need to enhance food quality monitoring, particularly in perishable goods such as meat. Traditional methods often fall short in identifying early signs of spoilage, and the integration of a CNN-based model fine-tuned through PSO offers a more accurate and efficient solution. The adoption of Python programming language, TensorFlow, and Google Colaboratory as the development environment underscores the commitment to open-source tools, promoting accessibility and collaborative innovation in the field of food safety. In essence, the hardware design, featuring a Raspberry Pi as the central controller, an LCD for intuitive output display, and a Pi Camera for capturing input images, emphasizes the user-friendly and practical nature of the system. By seamlessly integrating software and hardware components, the system not only showcases the prowess of modern technology in food safety but also serves as a testament to the potential for innovative solutions to address real-world challenges. As we navigate the evolving landscape of technology and food safety, this work contributes to the ongoing discourse on leveraging artificial intelligence and edge computing for the betterment of public health and consumer well-being.

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