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ADVANCES IN DEEP LEARNING TECHNOLOGIES FOR DETECTION AND CLASSIFICATION PROCESSES IN THE FOOD INDUSTRY

S u m m a r y

Background. Deep learning (DL) stands as a highly effective big data analytics method, boasting a remarkable track record across diverse domains such as image processing, voice recognition, object detection, illness diagnosis, prediction and clinical decision support systems. Its applicability extends even further into emerging areas like food science and engineering, where it has witnessed a surge in its application. Over the past decade, DL has demonstrated its utility in various facets of the food industry, including food quality assessment, the detection, differentiation, identification of diseases, phenotyping of plant stressors, monitoring and smart farming practices. The integration of DL technologies has been pivotal in revolutionizing the food business and its associated supply chains, facilitating advancements in food quality evaluation, food recognition and spectroscopic analysis. Notably, hyperspectral imaging and acoustic data have emerged as key modalities leveraged by DL techniques in these applications.

Results and conclusions. This study aims to delve into the recent strides made in Deep Learning frameworks within the food industry, exploring their diverse applications and functionalities. Of particular interest is the exploration of DL's role in food sensory analysis and consumer research, where it presents a promising avenue for sophisticated data mining techniques. Through a comprehensive examination of comparative performances, architectural nuances and potential future applications, this paper aims to shed light on the evolving landscape of DL in the realm of food science and engineering.

Keywords. deep learning, food quality, food classification

Introduction

A 'healthy diet' involves the all-essential nutrients that are helpful in maintaining the healthy lifestyle of individuals. WHO considers healthy food contains all nutrients such as fats, lipids, proteins, carbohydrates, macronutrients, micronutrients, essential oils, etc.; we know that everyone has busy schedule in their lives; there are about 3 trillion tons processed food sale all over the world and therefore most of people depend

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on industrial foods, drinks and other eatable things, hence it is important to provide healthy and clean food to people.

By keeping all these things in mind, WHO provides norms and rules for the food industries and companies such as the maintenance of healthy weightage of calories, suitable intake of fats, proteins and other nutrients, avoiding trans fats, maintaining sugar limit less than 10 % of calories, iodized salts, avoiding directly poisonous food, etc.; the food industries and companies are ready to agree to accept the norms and rules established by WHO. The food industries are a complex network of formation of processed foods, drinks and other eatable items. The food industries are not lonely works, they involve the collaboration of transportation, workers, digital media and the most important elements which are farmers, who provide raw materials for processed food. Farmers play an important role in this field and therefore apply the techniques which are followed by AI, DL and ML [29, 32, 40]. They use highly advanced technologies in their fields [12]. They use methods with AI algorithm for pest management [22]. The major useable crops such as wheat (18.3 %), rice (18.9 %), maize (5.4 %), potato (2.2 %) and soyabean (3.3 %) are taken by individuals on a very large scale throughout the world. The researcher assesses the data collected from the fields related to the burden of P&P at the global level that is based on less duration of time, i.e. almost three months. The assessment is done by the simple survey questionnaire method [20]. The research works discussed above, is divided into two parts; the first discusses crop loss caused by pathogens and pests based on crop positioning; while in the second part focuses of studying crops using national agricultural data within crops or intercrops to understand the relationship between crop productivity and losses with respect, to climate and food security. The global consumption of fruit will increase by 100 % to 150 % for 10 billion people globally by 2050 [30]. Because food is the cornerstone of human health, societal growth and stability, food quality and safety is a key issue for the entire society. Food quality and safety is a complex process that involves all stages of food processing, from agriculture, harvesting and storage through preparation and consumption [2, 10, 13]. Also, the loss of fruit and vegetables postharvest are in the range of 35 % to 55 % globally due to harvesting at wrong time, false identification of contamination, diseases and fruit bruises.

Nowadays, people are more concerned about their health and fitness, especially after the Covid pandemic [4]. People pay special attention to what they consume on a daily basis. The attention to food quality by people forces the food industry to obey strict food quality standards. Various ML- and DL-based technologies are used to maintain food quality [35]. These processes, on the other hand, are typically time-consuming. Advances in machine vision may now significantly assist researchers and businesses in increasing the efficiency of food preparation. As a result, machine vision is now widely used in the food business [19, 42]. Horticulture does also not remain effected by DL ML technologies for diseases detection, growth and monitoring of crops, vegetables, quality control and many more [7, 11]. This is not only helpful in uplifting the food related business, but also reduces the losses occurring from post harvesting issues and challenges. Various application of DL in the domain of food industry is shown in Figure 1.

Figure 1. DL applications in the domain of food quality [Own work]
Rycina 1. Zastosowania DL w obszarze jakości żywności [Opracowanie własne]

This review work summarizes some of the most effective ML and DL algorithms utilized in food processing and quality purpose. The paper is structured as follows: Section 1 introduces the technology of food processing and requirement of DL & ML algorithms in these industries. Further, in this section the DL models used specifically for Fruit processing and Quality control is discussed. Later in the section, various technologies, such as 3D imaging, acoustics and 2D RGB imaging for ML & DL models, are explained. Finally, the article ends with concluding the review of all the discussed DL & ML models.

State-of-the-Art Review

This section reviews some emerging and highly efficient algorithms which are utilized in the food processing industry. Machine learning algorithms have the potential to revolutionize the food industry by improving food quality, reducing waste and enhancing customer experience. This abstract provides an overview of the current applications of machine learning in the food industry, including food processing, food safety and food marketing. Machine learning algorithms can be used to predict the quality of raw materials, optimize processing conditions and identify potential defects in food products. Additionally, machine learning algorithms can be used to monitor food safety and detect potential contaminants in real time. By leveraging this technology, food manufacturers can reduce waste and increase efficiency, resulting in cost savings. Machine learning algorithms can also be used to analyze consumer data and preferences, allowing companies to develop personalized marketing campaigns and create new products tailored to specific customer needs. This approach can enhance the customer experience and increase customer loyalty.

Emerging Deep Learning Algorithms in Fruit Processing Industries

Food processing is the transformation of raw materials such as natural animals and plants into food, or the transformation of one type of food into another that is more suited to contemporary dietary requirements [25, 38]. The quality of fruit is a crucial factor that impacts its commercial value and consumer acceptance. With the advancement in technology, machine learning algorithms have emerged as a promising approach to improve the quality of fruit. In this work, we will discuss various methods of increasing the quality of fruit using Deep Learning (DL) algorithms.

One method is to use image processing techniques to analyze the external features of fruit, such as color, size and shape. Machine learning algorithms can then be used to develop models that correlate these features with the internal quality attributes of fruit, such as sweetness, acidity and firmness. This information can be used to sort fruit according to its quality and optimize the packing process.

Deep Learning Algorithms Based on 3D Scan Techniques in Food Processing:

One of the most popular fruit types, with production of more than 84 million tons, are apples. They occur in a large range of varieties depending on their color, size, shape and presence/absence of certain features [8, 15]. Apple farming requires certain temperature, soil condition and humidity. Most apples during harvesting time get bruised and start to rot, affecting thus other fresh apples and reducing the fresh apples quantity. Bruises act as a pathway for oxygen to react with polyphenols which start the degradation of apples. Hu et al [31] proposed DL and CNN based predictive model for detecting bruised apples. The model used 3D scans generated from infrared images for the detection of bruised apples. Simply analyzing 2D images of apples or visuals do not allow high accuracy of the detection of bruises on apples. Thus, the need of analyzing 3D images is a prime requirement. The earlier use of 2D scanning systems like X-ray, MRI, near infrared imaging, thermal imaging, etc. was possible but was constrained by limited or low accuracy, viewpoint high sensitivity and poor bruised depth identification capabilities. In order to overcome these challenges, 3D Near Infrared sensing (NIR) has been developed; in addition to that, it does not harm tissue, it is more user friendly [3]. Three-dimensional images are generally presented by a polygon surface mesh. They are difficult to adopt by 2D shape analysis techniques. Thus, 3D shape descriptors are used, such as Mesh HoG and SIFT Heat Kernel Signatures

(HKS). Although 3D shape descriptors are effective, they increase the process length by domain knowledge and trial & error process. CNN has a proven record in processing images, detection, segmentation, retravel and recognition in various domains [18]. However, most of the CNN-based models find it difficult to interpret or learn features directly from 3D structures. A few CNN models, such as Multiview CNN, also known as MVCNN, are capable of 3D image recognition. In this methodology, a 3D image is converted into 12 2D images followed by rendering of each image by trained CNN to obtain multi-layer feature representation of the image. In earlier works, the CNN models do not use pooling layers with constrained size, which allows the loss of surface information during the processing. In this work, the author uses the 3D spatial technology-based sensors for scanning granny smith apples using a triangulated mesh model based 2D feature images followed by the application of apple bruise identification block which categorizes apples into bruised and non-bruised ones [1].

The author in [39] used AlexNet-based end-to-end training CNN model called CNN-ENE, with the use of connected BN layer adjacent to convolutional layer and pooling layers. The model consists of five convolutional layers, three pooling layers, three fully connected ones, eight ReLU activation ones, five batch normalization layers and a SoftMax layer. Another developed model makes use of VGG 19 CNN-based model for maintaining consistency. Pre-trained VGG 19 make use of 19 convolution, five max pooling, three connected, 18 ReLU activation, two dropout layers and a SoftMax output layer. Both models extract 2,048 and 4,096 features respectively. Inception V3 model is also developed, making use of 103 convolutional, four max pooling, and ten average pooling layers model to extract 2,048 features. Additionally, the author applies feature fusion and decision fusion strategies for boosting the model performance. A dataset of 302 apples was used, out of which 272 for training and the remaining ones for testing purposes. The performance of the model is compared on the basis of local feature descriptors such as maximum curvature (denoted by *MaxC*), minimum curvature (denoted by *MinC*), mean curvature (denoted by *MeanC*), Gaussian curvature (denoted by *GauC*), shape index (denoted by *ShapeI*), curvature index (denoted by *CurI*), distance between the vertices in the mesh and the geometric center (i.e. centroid) of the mesh (*Rad*). These parameters are evaluated and compared for Accuracy, Precision Recall (*PR*), *F1* score and *ROC* [36]. The CNN-ENE model based on nine single channel feature maps was evaluated as shown in Figure 2.

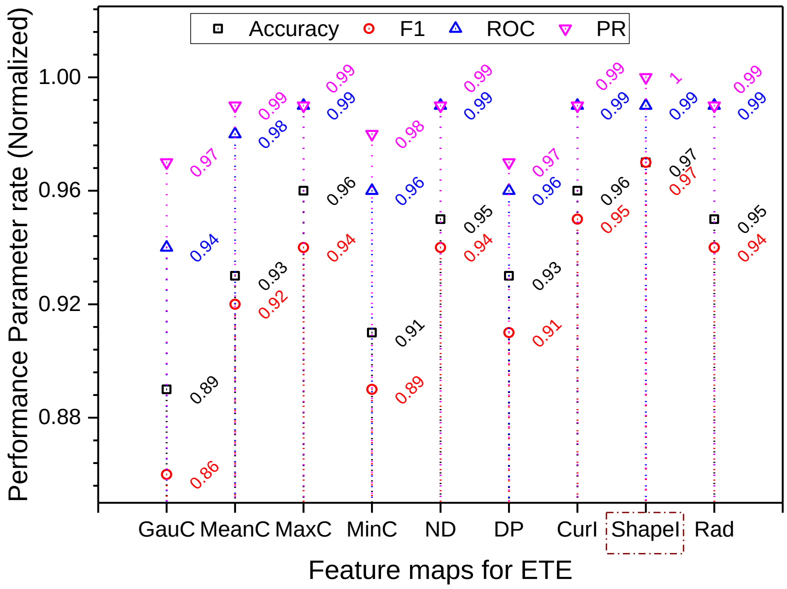

Figure 2. Performance parameters of CNN ETE model for different feature maps
Rycina 2. Parametry wydajności modelu CNN ETE dla różnych map cech

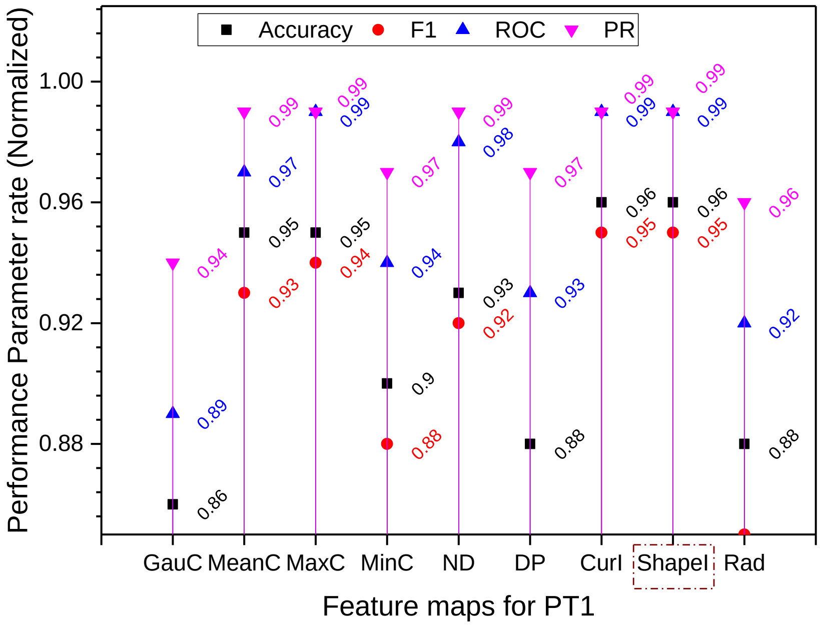

Figure 3. Performance parameter of VGG 19-based PT1 model for different feature maps
Rycina 3. Parametr wydajności modelu PT1 opartego na VGG 19 dla różnych map cech

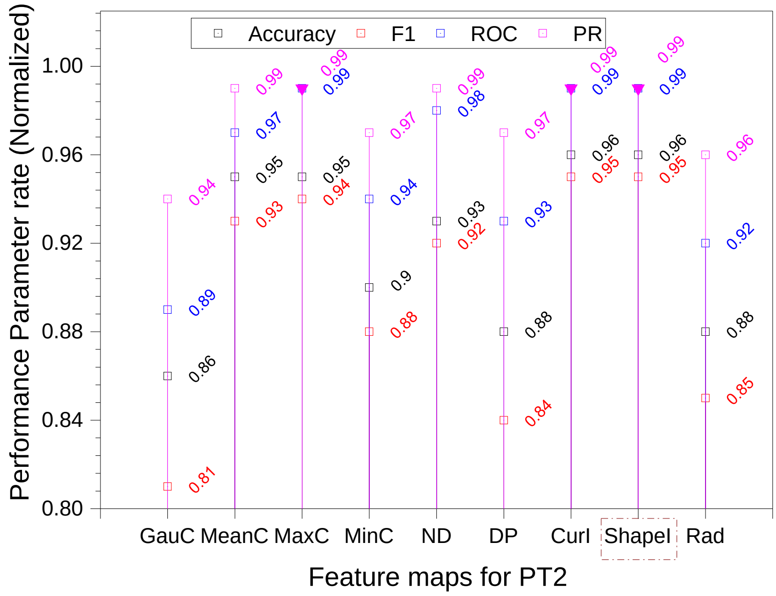

Figure 4. Performance parameter of InceptionV3-based PT2 model for different feature maps
Rycina 4. Parametry wydajności modelu PT2 opartego na InceptionV3 dla różnych map cech

Figure 3 and Figure 4 compares various parameters for VGG 19-based PT1 model and InceptionV3-based PT2 model. It can be observed that Inception V3 model outperformed other feature-based models with accuracy of above 97 %. The performance of the inception V2-based PT2 model was evaluated on a separate dataset of apples, and the results showed that the model could accurately identify bruises with a precision of 92.2 % and a recall of 92.3 %. This indicates that the model has a high ability to correctly identify both true positive and true negative samples and can effectively differentiate between bruised and non-bruised apples as compared to other models. Overall, the Inception V3-based PT2 model demonstrated strong potential in predicting bruises on apples, which can help improve the quality control and grading processes in the fruit industry. However, further testing and optimization may be required to ensure its reliability and accuracy in real-world settings. Further, the model can be used for other applications like grading of apples and detection of bruises on fruit in general.

Deep Learning Algorithms Based on Acoustic Techniques in Food Processing:

As a result of growing environmental pollution, people are concerned about the safety of both food sources and food processing procedures [26, 28]. It is critical to ensure that the nutritional properties of raw materials are retained throughout processes and that no harmful or toxic substances are introduced into food [36, 37]. A CNN approach has been used for the detection of mealiness and non-mealiness in apple fruit by Lashgari et al [15]. He developed a nondestructive approach by using acoustic sensing and CNN. The storage of apples under different conditions of temperature and humidity led to softening and dry texture, thereby making apples look mealy. Other factors, including harvesting time, fruit size and storage time, also affect the mealiness of apples. Thus, apples require a rapid assessment for maintaining good quality. Various methods of testing apple mealiness include mechanical, ultrasonic, force impulse, MRI, NIR spectroscopy, florescent methods, and many more. However, in the present case, the author used acoustic methods, which are nondestructive, cost effective and rapid in nature. A plastic pendulum is dropped on an apple from a certain height. The sound is recorded and converted into 2D images. Subsequently, the proposed model is used to classify if the apple is mealy or not. For experimentation, 180 apples, which were freshly harvested and stored under different conditions of temperature, humidity and storage time, were selected. In this work, the author uses eight layers of AlexNet, five layers of *Conv* (Convolutional) and three fully-connected layers (FC layer). The *Conv* layer is the main part of the structure; its kernels (or filters) perform convolutional operation on the input image and create output image representations (i.e. feature maps). The pooling layer follows a *Conv* layer and reduces the dimension of the feature maps, number of parameters and training time.

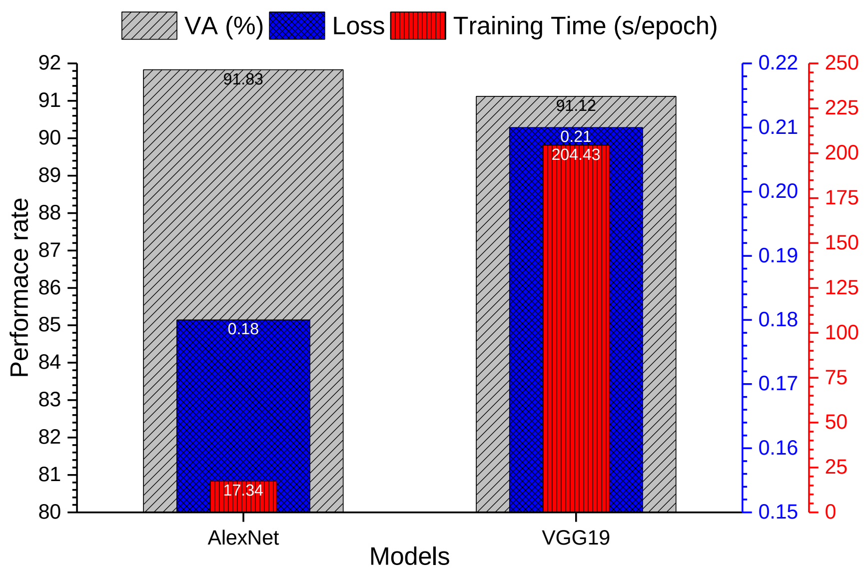

Figure 5. The average validation accuracy, loss and processing time for AlexNet and VGG19 for an average of 12 apples and 40 training epochs

Rycina 5. Średnia dokładność walidacji, strata i czas przetwarzania dla AlexNet i VGG19 dla średnio 12 jabłek i 40 epok szkoleniowych

The activation function, such as Rectified Linear Units (ReLU), is applied to every *Conv* and FC layer. On the other hand, the VGG19 model is also proposed with 16 convolutional, five max pooling layers, three FC layers and a SoftMax layer. A dataset with 70 % training and 30 % validation proportion is used and repeated ten times to improve mean validation accuracy and reduce training time and loss. The proposed model is also compared with the leading models and frameworks present in the market for comparison. To acquire the original mealiness of apples, they were tested by destructive testing. The average validation accuracy, loss and processing time was calculated for both AlexNet and VGG19, as presented in Figure 5 for an average of 12 apples and 40 training epochs.

Average classification accuracy, validation accuracy training time and classification time calculated for the best settings is presented in Figure 6. The comparative performance is also shown in Figure 6, which shows that the models (specifically AlexNet) performance is fairly well compared to others models.

Moreover, this model is capable of quantifying mealiness levels within small variability in mealiness within a group. This method is less expensive, more rapid and simple, yet a robust tool for monitoring fruit quality of sorted fruit under different conditions of temperature, humidity and time. This model can help in deciding parameter to choose optimum time for the harvesting of apples. This technique proves to be cost effective, nondestructive testing technique and can be used for other varieties of apples and, in general, fruit.

Deep Learning Algorithms Based on Hyper-Spectral Imaging (HPI) Techniques in Food Processing:

Another nondestructive technique of fruit quality control is hyper-spectral imaging. This includes the use of a wide spectrum of rays to detect various features in fruit, such as infrared and ultraviolet rays spectrum. Enabling hyper-spectral imaging (HPI) technique with AI and DL has been extensively used in the domain of remote sensing, the agriculture recycling industry, the medical industry and many more [9, 16]. The proposed model of integrated Hyperspectral imaging and DL for detection of ripening stages of kiwi and avocados was presented by Varga et al. [34]. Earlier, HPI had been alone used for firmness, soluble solid content and ripening of tomatoes. In this work, the author presented a model integrating HPI and DL for monitoring kiwis and avocados by identifying the soluble solid content and firmness of fruit. The data of 1,038 avocados and 1,522 kiwis recorded by an HPI camera were analyzed. The dataset was divided randomly into 80 %, 10 % and 10 % for training, validation and testing purposes. The main objective was to identify if fruit was ripe, unripe or overripe. The

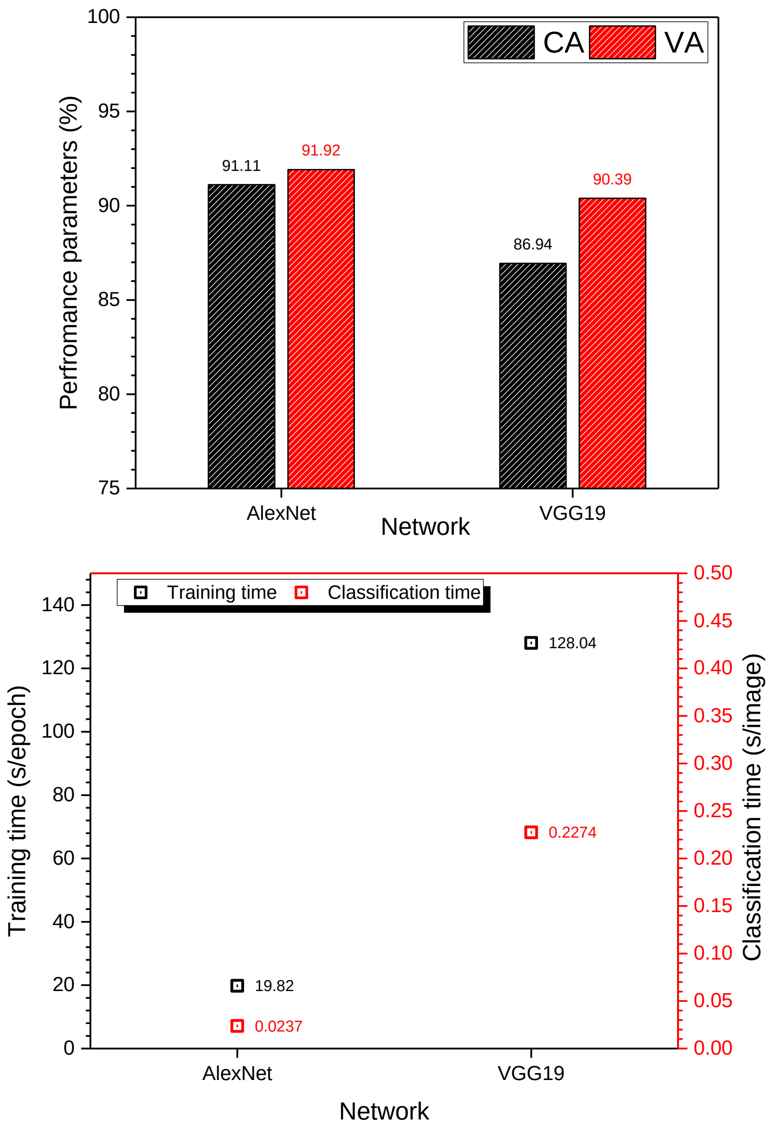

Figure 6. Average classification accuracy, validation accuracy training time and classification time calculated for the best settings

Rycina 6. Średnia dokładność klasyfikacji, czas treningu dokładności walidacji i czas klasyfikacji obliczone dla najlepszych ustawień

proposed HIP CNN model uses three Convolution layers, one average pooling, one batch normalizing and one fully connected layer to make the model less complex, yet more effective. The proposed model was compared with a similar model, such as SVM, KNN ResNet 18, AlexNet for accuracy in determining the firmness, ripeness and sweetness of both avocado and kiwi. Figure 7 shows performance results for hyper spectral imaging for Avacado and Kiwi fruit.

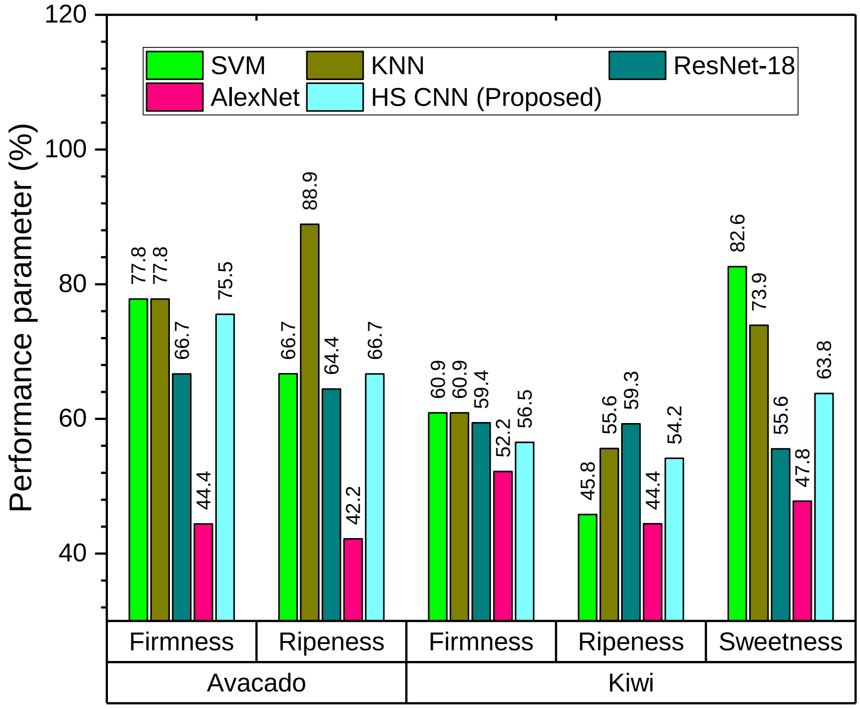

Figure 7. Hyperspectral imaging for Avocado and Kiwi fruit
Rycina 7. Obrazowanie hiperspektralne owoców awokado i kiwi

The proposed model predicts the firmness and ripeness of avocado by 93.33 % and 90 % respectively. Kiwis were slightly difficult to be accurately predicted with 70 % firmness and 80 % ripeness accuracy. The proposed model performs well above the baseline models in classifying fruit into unripe, ripe and overripe fruit with high accuracy.

Deep Learning Algorithms Based on 2D RGB Imaging Techniques in Food Processing:

Another fruit, banana, is popular in tropical and sub-tropical regions of the globe. While ripe bananas are sweat and tasty to eat, unripe bananas are full of starch and other micronutrients, which are useful for human functioning [21]. India is a leading producer of bananas worldwide and the main exporter of bananas. However, banana crops face major losses in postharvest due to bananas' delicate structure and low shelf life stability, packaging and transport [6]. Technology has provided solutions to mitigate such losses. Manual classification is cost effective, but poor in performance. Effective solutions are destructive testing in nature and random sampling. The best solution is the non-invasive method based on image recognition and deep learning models [23]. One such framework was proposed by Mesa et al [27], which utilizes RGB imaging scheme integrated with deep learning for classification of banana tiers. The proposed model makes use of transfer learning and VGG 16 Deep CNN framework for classifying bananas into four categories and ten subcategories, namely banana quality (export, middle and reject class), banana maturity (overripe, yellow, turning yellow and green) and banana size (small, medium and large). The proposed model makes use of a few images of the samples for banana grading, which makes it cost effective and rapid compared to other models. The model considers 1,766 images of banana clusters for grading bananas into four categories and ten subcategories. The batch size of 32 image datasets were considered with an epoch varying between 30 to 100 depending upon the categories. The performance parameters of the model are shown in Figure 8.

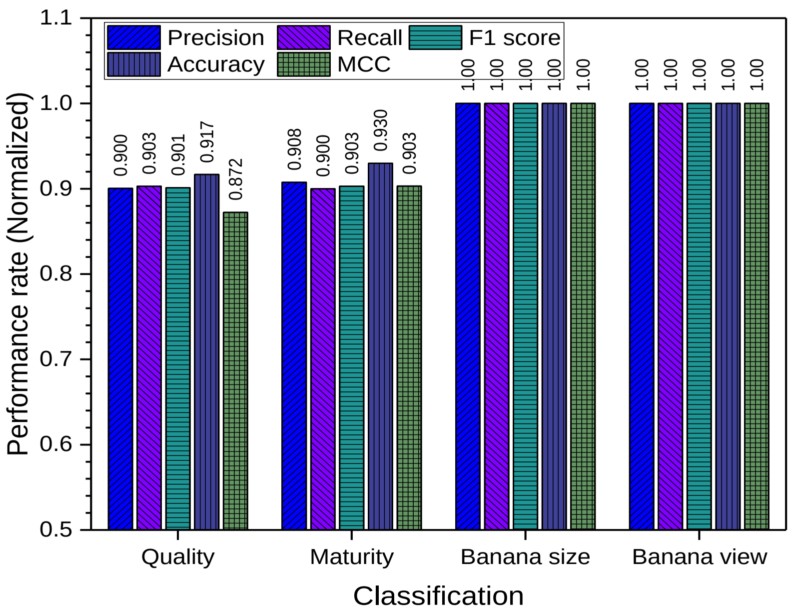

Figure 8. Performance parameters for various classification activities of banana fruit
Rycina 8. Parametry wydajności dla różnych działań klasyfikacyjnych owoców banana

The model tends to perform well in terms of *Precision*, *Recall*, *Accuracy* for the banana grading system. Previously built models make use of K-means clustering, ANN, Fuzzy logic-based models for banana finger or single banana for fruit classification, fruit maturity and fruit grading, which is practically inefficient due to the fact that banana is harvested, transported in tiers or banana hands or clusters. Roy et al [24] worked on the comparison of deep learning algorithms which are able to differentiate between rotten and fresh fruit before eating. According to the researcher, it is possible by applying the RGB images of fruit (rotten and fresh fruit) in deep learning algorithms such as UNet and EnUNet. As far as this method is concerned, the two models are compared in the form of two metrices; accuracy and Intersection over Union (IoU) scores, IoU is also known as Jaccard index. The working of these models is done in Google Colabs with GPU Tesla K80 [Extra]. The experiment shows that the EnUNet algorithm performs better for classification between fresh and rotten fruit than the UNet algorithm. The results of these two algorithms are shown in Figure 9. As demonstrated in Figure 9, the accuracy values for EnUNet are equal to around 97.5 %, the IoU values 0.886 % and the UNet algorithm achieves the accuracy level of approx.. 94 ÷ 95%. The comparison shows the superiority of EnUNet over other algorithms. Hence, this method can be applied in a number of food processing industries in the future.

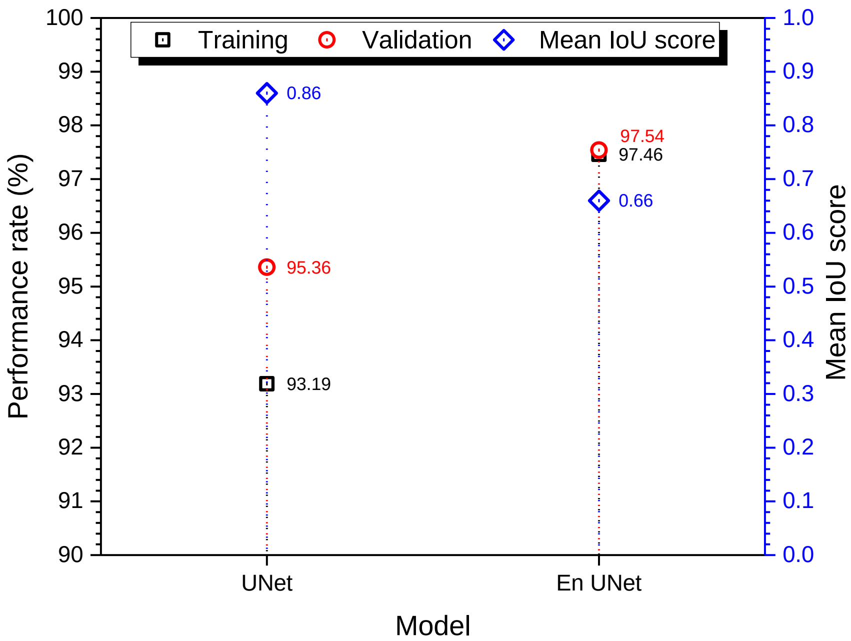

Figure 9. Comparison of UNet and En UNet models for training accuracy, validation accuracy and mean IoU score

Rycina 9. Porównanie modeli UNet i En UNet pod kątem dokładności treningu, dokładności walidacji i średniego wyniku IoU

Agricultural productivity highly affects production of the food industries. Agricultural products face various difficulties, such as floods, drought, ill-irrigation, pest attacks. One major issue of degradation in crop production is diseases. According to a survey by Savary et al [33], there is about a 21.5 % yield loss due to several crop diseases. If these problems are not solved in time, then they damage the overall crop yields. Oishi [17] et al proposed a model which is able to easily identify abnormally seeded potatoes. The researcher compares the deep learning algorithms for the detection of clear and accurate images of infected leaves with and without pre-processing. The comparison is done between the Average Precision (AP) YOLO and R-CNN. The Figure shows that the model R-CNN provides accurate images with high accuracy as compared to YOLO. Figure 10 also demonstrates that values for R-CNN remain the same with and without pre-processing, standing nearly at about 94.2 % without pre-processing and 90.2 % with pre-proceeding. Figure 10 also compares the average precision in abnormal plant detection of YOLO and R-CNN.

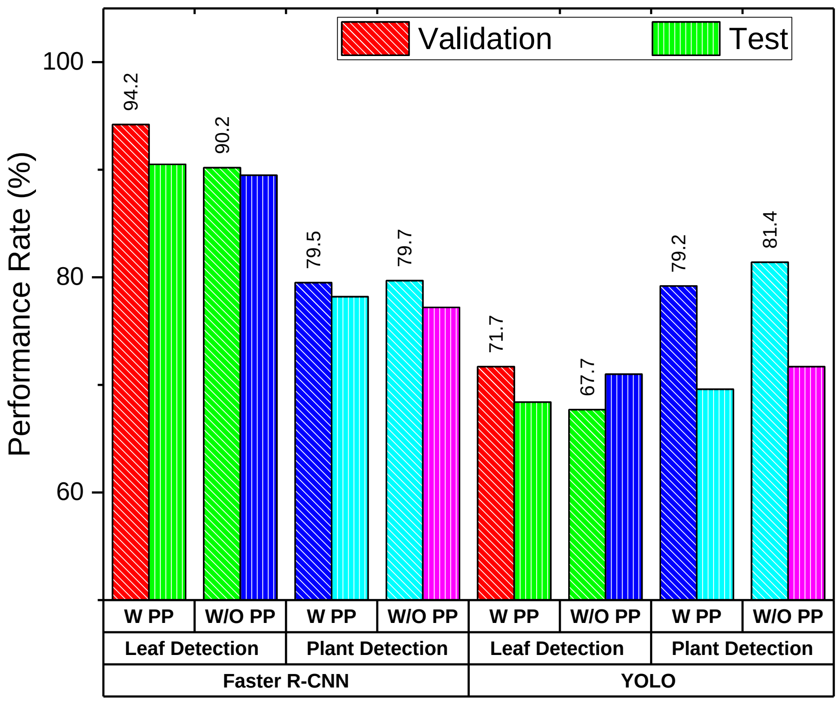

Figure 10. Validation and Testing the accuracy of the proposed models with and without pre-processing images in diseased leaf and plant detection for potato crop plant

Rycina 10. Walidacja i testowanie dokładności proponowanych modeli z obrazami poddanymi wstępnemu przetwarzaniu i bez nich w wykrywaniu chorych liści i roślin w uprawie ziemniaka

As showed by this analysis, the model R-CNN can be applied for the detection of abnormal potato plants. There is a large number of varieties produced in agricultural labs as per need i.e., high yield productivity, disease free, easily cultivation, zero pest attacks seed for various crops such as wheat, rice, maize, potatoes, soyabeans, etc. Therefore, many researchers are working on the identification of good qualities of crops which are important for the farmers who provide raw materials to food companies and food industries. Laabassi et al [14] works on the identification of good varieties of wheat, using various algorithms and frameworks on the basis of deep learning. The researchers discuss how machine learning, artificial intelligence and deep learning work in classifying wheat varieties with the help of RGB images. RGB images are also applicable for identifying diseased seeds. The models classify wheat varieties with accurate percentage values of between 94 % to 95 %, which are based on the CNN.

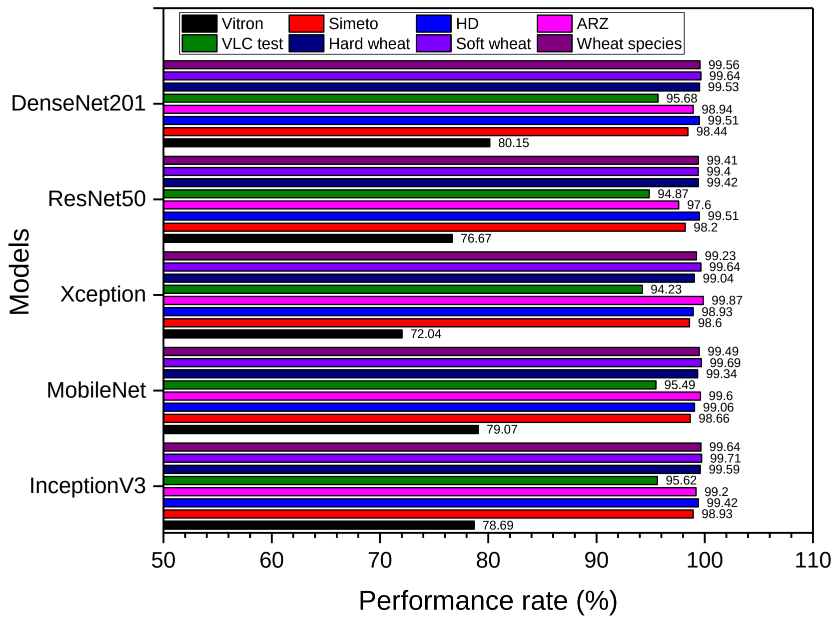

Figure 11. Comparative performance of the proposed model with other models in identifying different wheat varieties

Rycina 11. Porównanie wydajności proponowanego modelu z innymi modelami w identyfikacji różnych odmian pszenicy

For the classification, first of all, data is collected using the 2D dorsoventral grain RGB images of wheat plants, and subsequently, deep learning is applied on the selected data [5]. The whole data undergoes the segmentation process in which images are cropped into relevant images, and subsequently, under the next step, deep learning models are applied. There are five types of frameworks applied on these images, namely; MobileNet, xception, inceptionV3 ResNET50 and DenseNet 201. As illustrated in Figure , the MobileNet and DenseNet 201 frameworks provide accurate knowledge with 80.10 % accuracy, MobileNet (98.66 %) and Xception (98.60 %) accuracy. Hence, we can say that the inceptionv3, MobileNet and DenseNet are the best deep learning models that can classify the variety of wheat with accuracy. And finally, out of the three models, the inceptionV3 model provides the most accurate values.

Conclusion and Future Scope

In the field of food quality, machine learning (ML) has demonstrated significant promise, surpassing more conventional techniques like fuzzy logic systems. Deep learning (DL) provides an autonomous learning characteristic that enables the retention of information learned after training, in contrast to traditional machine learning (ML). Because typical ML algorithms do not have this property, DL is a viable method for assessing food quality.

The development of affordable imaging equipment for hyperspectral imaging (HSI) data collection, coupled with adequate computational resources, is a noteworthy accomplishment in this sector. With the use of these technologies, it is possible to apply ML and DL models to assess different quality parameters in important crops like rice and wheat, as well as in widely consumed fruit like bananas, apples and mangoes.

The models that were built exhibited exceptional efficacy in categorizing fruit and plants based on their quality, size, ripeness, mealiness, grade identification and ability to identify illnesses and infections. To ensure food quality, real-time application optimization is critical; yet, the intricacy of ML and DL models poses difficulties. To fully realize the promise of DL technologies in the food business, despite the progress made, a number of restrictions and problems still need to be resolved.

Challenges and Limitations

Accessibility and Caliber of Data:

Robust deep learning models require large, high-quality datasets for training. It can be difficult to obtain large datasets that fairly depict the variety of dietary items and circumstances, though. Another challenge is to guarantee data quality and consistency across many sources and circumstances.

Model Interpretability and Complexity:

Deep neural networks in particular, which are DL models, may be extremely complicated, making them challenging to read and comprehend. The use of these technologies in the industry, where comprehension of the decision-making process is essential, may be hampered by this lack of transparency. One important area of study to increase the usability and accessibility of these technologies is simplifying models without sacrificing performance.

Computational Requirements:

Training and deploying DL models require significant computational resources, which may not be feasible for all stakeholders, especially small-scale producers and farmers.

Developing more efficient algorithms and hardware solutions to reduce computational costs and improve accessibility is essential.

Real-Time Processing:

Achieving real-time processing and analysis is critical for practical applications in food quality assessment. However, the current models often require substantial processing time, which can limit their effectiveness in real-world scenarios.

Research should focus on optimizing DL models for faster inference times without sacrificing accuracy. To tackle these obstacles, next studies ought to concentrate on:

- Improving techniques for gathering data and building sizable, excellent datasets to aid in the creation of reliable deep learning models.
- Creating DL models that are more easily interpreted, streamlined and practical.
- Increasing processing efficiency with improved hardware and techniques.
- Concentrating on real-time processing power to provide useful applications in food quality monitoring.
- Investigating methods for adaptive learning to enhance the generalization and flexibility of models.
- Developing affordable solutions that allow all parties involved in the food business to utilize the DL technology.
- Food quality evaluation may be greatly advanced by the DL technologies by tackling these issues, guaranteeing safer and better-quality food items for customers all over the world.

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POSTĘP W TECHNOLOGIACH GŁĘBOKIEGO UCZENIA SIĘ STOSOWANYCH W PROCESACH WYKRYWANIA I KLASYFIKACJI W PRZEMYŚLE SPOŻYWCZYM

S t r e s z c z e n i e

Wprowadzenie. Głębokie uczenie się (Deep Learning) to wysoce skuteczna metoda analizy dużych zbiorów danych, mogąca poszczycić się niezwykłymi osiągnięciami w różnych dziedzinach, takich jak przetwarzanie obrazu, rozpoznawanie głosu, wykrywanie obiektów, diagnozowanie chorób, przewidywanie i systemy wspomagania decyzji klinicznych. Jej zastosowanie rozciąga się jeszcze dalej na nowe obszary, takie jak nauka o żywności i inżynieria, gdzie nastąpił gwałtowny wzrost jej wykorzystania. W ciągu ostatniej dekady technologia DL wykazał swoją użyteczność w różnych aspektach przemysłu spożywczego, w tym w ocenie jakości żywności, wykrywaniu, różnicowaniu, identyfikacji chorób, fenotypowaniu roślinnych czynników stresogennych, monitorowaniu i inteligentnych praktykach rolniczych. Integracja technologii DL odegrała kluczową rolę w zrewolucjonizowaniu branży spożywczej i powiązanych z nią łańcuchów dostaw, ułatwiając postęp w ocenie jakości żywności, rozpoznawaniu żywności i analizie spektroskopowej. Warto zauważyć, że obrazowanie hiperspektralne i dane akustyczne okazały się kluczowymi metodami wykorzystywanymi przez techniki DL w tych zastosowaniach.

Wyniki i wnioski. Celem tego opracowania jest ocena ostatnich postępów w zakresie rozwiązań DL w przemyśle spożywczym, zbadanie ich różnorodnych zastosowań i funkcjonalności. Szczególnie interesująca jest ocena roli DL w analizie sensorycznej żywności i badaniach konsumenckich, gdzie stanowi ona obiecującą drogę dla wyrafinowanych technik eksploracji danych. Poprzez wszechstronne badanie porównawcze wydajności, niuansów architektonicznych i potencjalnych przyszłych zastosowań, niniejszy artykuł ma na celu rzucić światło na ewoluujący obraz DL w dziedzinie nauk o żywności i inżynierii.

Słowa kluczowe: głębokie uczenie się, jakość żywności, klasyfikacja żywności