


Article

Enhanced Occupational Safety in Agricultural Machinery Factories: Artificial Intelligence-Driven Helmet Detection Using Transfer Learning and Majority Voting

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Abstract: The objective of this study was to develop an artificial intelligence (AI)-driven model for the detection of helmet usage among workers in tractor and agricultural machinery factories with the aim of enhancing occupational safety. A transfer learning approach was employed, utilizing nine pre-trained neural networks for the extraction of deep features. The following neural networks were employed: MobileNetV2, ResNet50, DarkNet53, AlexNet, ShuffleNet, DenseNet201, InceptionV3, Inception-ResNetV2, and GoogLeNet. Subsequently, the extracted features were subjected to iterative neighborhood component analysis (INCA) for feature selection, after which they were classified using the k-nearest neighbor (kNN) algorithm. The classification outputs of all networks were combined through iterative majority voting (IMV) to achieve optimal results. To evaluate the model, an image dataset comprising 662 images of individuals wearing helmets and 722 images of individuals without helmets sourced from the internet was constructed. The proposed model achieved an accuracy of 90.39%, with DenseNet201 producing the most accurate results. This AI-driven helmet detection model demonstrates significant potential in improving occupational safety by assisting safety officers, especially in confined environments, reducing human error, and enhancing efficiency.

Keywords: OHS; PPE; farm machinery factories; industrial safety; transfer learning; iterative neighborhood component analysis; k-nearest neighbor; IMV



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1. Introduction

In addition to water and energy resources, humans represent a crucial resource for sustainable agriculture [1]. However, the health of those working in the agricultural sector has not been sufficiently prioritized. Agriculture is one of the four most hazardous sectors globally, along with construction, industry, and medicine [2]. A variety of ergonomic risks [3] and exposure to agricultural chemicals [4] have been identified as potential hazards during agricultural operations. However, the principal reason for agriculture's categorization as one of the most hazardous sectors is the occurrence of accidents associated with the manufacture and operation of tractors and agricultural machinery [5]. The advancement of agricultural mechanization has played a pivotal role in enhancing agricultural productivity [6]. It is evident that the utilization of emerging technologies, such as the operation of pesticide applications via agricultural drones, has the potential to mitigate specific risks [7]. However, it has also been demonstrated that the incidence of accidents rises in line with the progression of mechanization [8]. As is the case in all sectors, the human factor plays a significant role in determining the likelihood of hazards becoming risks in agriculture. This is influenced by factors such as age, education, and experience [9]. In particular, the failure to utilize personal protective equipment (PPE) represents a significant challenge to occupational safety, underscoring the necessity for rigorous supervision [10].

The necessity of helmet use in occupational health and safety is underscored as a pivotal concern, particularly in high-risk work environments. The deployment of helmets is of paramount importance in safeguarding worker safety, as it markedly diminishes the likelihood of head and brain injuries [11].

Artificial intelligence (AI) is a field of study that has been the subject of considerable attention in recent years, with a particular focus on its potential to enhance productivity in agricultural contexts [12]. However, it is also a technology that has the potential to revolutionize the field of occupational health and safety [13]. Despite the effective use of AI and machine learning methods in various sectors, studies focusing on occupational health and safety remain limited.

Artificial intelligence (AI) technologies have a significant impact on the detection and analysis of risks in the workplace. The utilization of sophisticated algorithms enables AI to process extensive datasets and discern intricate patterns. Such capabilities may be deployed to identify potential hazards and risks in the workplace. To illustrate, AI-based image recognition models can monitor the correct use of protective equipment by employees, such as helmets, goggles, or ear protection, and issue warnings if such equipment is absent [14].

Artificial intelligence can be employed as a valuable tool to enhance workplace safety, reduce risks, and prevent accidents. These technological advancements can make a significant contribution to enhancing workplace safety and efficiency [15]. In particular, the absence of AI-based applications designed to guarantee worker safety represents a significant gap in the existing literature, particularly in specific fields, such as tractor factories [16]. There is a paucity of AI-based models that support occupational health and safety in specialized industries, such as facilities producing tractors and agricultural machinery. In a recent study, Tan et al. (2021) [17] employed machine learning algorithms utilizing microelectromechanical system (MEMS)-based sensors to ascertain the extent of helmet utilization on construction sites. The objective of their research was to develop a real-time, automated helmet detection model to enhance workplace safety and compliance monitoring. Similarly, Nath et al. (2020) [18] employed deep learning techniques to detect personal protective equipment in real time, thereby demonstrating the potential of AI-based visual recognition models in identifying workers' use of helmets and other safety equipment. Most existing studies are limited in scope, focusing on established machine-learning techniques without delving into the intricacies of deep feature extraction methodologies and combinational approaches. In a related study, Hayat and Morgado-Dias (2022) [19] developed an AI-driven model for helmet detection in construction, utilizing image processing techniques to enhance safety practices within the industry. The majority of studies are conducted by computer scientists alone, with insufficient incorporation of the perspectives of occupational health and safety experts. These gaps underscore the need for a robust and accurate AI-based model to detect helmet usage, addressing specific challenges in agricultural machinery factories and improving occupational safety standards. Han and Zeng (2021) [20] put forth a deep learning model that employs multi-scale features for helmet detection, underscoring the potential of AI in automating safety monitoring in the workplace. Campero-Jurado et al. (2020) [21] devised an "Intelligent Helmet 5.0" for the Industrial Internet of Things (IIoT) to improve worker safety by providing real-time alerts regarding environmental hazards. In a review of the literature on multi-sensor smart helmets, Lee et al. (2022) [11] explored the potential of these devices for monitoring workers' health and detecting potential hazards. In a similar vein, Kim et al. (2019) [22] developed a computer vision model utilizing deep learning algorithms to automatically ascertain whether construction workers were wearing helmets, thereby exemplifying the efficacy of AI in guaranteeing safety compliance. Moreover, Yu et al. (2022) [23] investigated the real-time detection of personal protective equipment through the utilization of hybrid machine-learning techniques, emphasizing the potential of AI in monitoring safety compliance. In their 2018 study, Wu and Zhao [24] proposed a novel image-based approach for helmet detection, utilizing artificial intelligence (AI) to enhance safety standards in work environments. Wang et al. (2021) [25] developed a deep-learning model for helmet

detection and worker identification in construction and industrial environments, thereby demonstrating the potential of AI to enhance safety management. Li et al. (2014) designed a smart safety helmet integrating IMU and EEG sensors to detect worker fatigue, thereby underscoring the importance of monitoring physical conditions in occupational safety [26]. Shen et al. (2021) put forth a deep transfer learning approach for helmet detection, thereby offering an effective method for enhancing helmet use compliance in construction [27]. Moreover, Li et al. (2020) [28] developed a model that combines online hard example mining and multi-part combinations for helmet detection, thereby exemplifying the role of AI in identifying safety violations. In a related vein, Nath and Behzadan (2020) [29] examined the potential of deep learning for the automatic identification of personal protective equipment, with a view to enhancing workplace safety. Kwak and Kim (2022) [30] concentrated on the YOLOv5-S model and transfer learning for helmet detection, concluding that the model is an effective means of ensuring safety at construction sites. Lastly, Padmini et al. (2020) [31] developed a real-time system for detecting motorcycle helmet use, thereby demonstrating the application of image processing and AI in enhancing traffic safety. Similarly, Kim and Choi (2022) [32] explored a proximity warning model for road safety using intelligent helmets, thereby highlighting the potential for AI-based safety alerts. In a recent study, Lee et al. (2023) [33] conducted a comparative analysis of convolutional neural network (CNN) algorithms for two-stage helmet detection, with the objective of evaluating the performance of different artificial intelligence (AI) models in supporting occupational safety standards.

In light of these considerations, the objective of this study was to develop an AI model that can accurately ascertain whether individuals engaged in the operation of tractor and agricultural machinery facilities are wearing the requisite personal protective equipment, namely helmets. Therefore, this study sought to incorporate the insights of occupational health and safety experts into a comprehensive approach.

2. Materials and Methods

In this study, the dataset was obtained from open sources and tractor manufacturers. The dataset comprises images in the JPG and PNG formats. Two classes, named “with helmet” and “without helmet”, were created within this dataset. To ensure the dataset’s suitability for real-world applications, images were captured from various angles and positions, thereby reflecting real-world scenarios (Figure 1).

The composition of the dataset, comprising images taken from actual work environments, clearly demonstrates the feasibility of the proposed method for real-time use. The images used in this study were obtained from agricultural machinery and tractor manufacturing facilities. It is important to note that each manufacturing facility may have different conditions, adherence to safety protocols, and compliance rates, which could vary based on the specific machinery produced. As researchers, we recognize that it is not feasible to control these variables across all manufacturers, which may introduce some variability in the dataset. The dataset comprises 662 images of helmeted individuals and 722 images of unhelmeted individuals. Although the dataset size is limited, it was selected to reflect real-world scenarios, incorporating images with varying angles and lighting conditions.

In this study, a novel transfer learning-based model was developed. The model comprises four principal stages: feature extraction, feature selection, classification, and weighted voting. The initial stage of the developed model is feature extraction, which employs pre-trained deep convolutional neural networks (CNNs). The convolutional neural networks (CNNs) utilized were previously trained on a dataset, ImageNet1k, comprising approximately 1.3 million images of 1000 distinct objects. The choice of nine pre-trained networks was made to ensure diverse feature extraction capabilities, as these networks are known for their strengths in different contexts, such as object detection, efficiency, and depth.

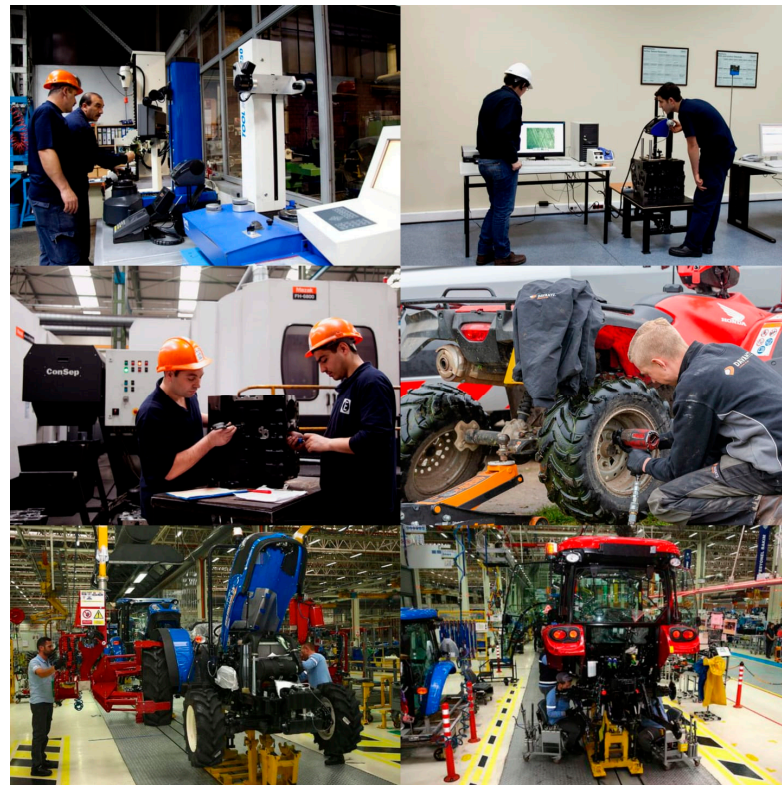


Figure 1. The visual materials utilized in the analytical process.

The MobileNetV2 model is a convolutional neural network designed by Google researchers with the objective of achieving greater efficiency, making it suitable for use in mobile and embedded vision applications. MobileNetV2, designed by Google researchers, is a convolutional neural network with a focus on efficiency, rendering it suitable for deployment in mobile and embedded vision applications. The main features of the network are as follows [34]. The model has been optimized for both computational efficiency and model size without a significant reduction in performance. This architectural style is optimal for on-device applications where computing resources are constrained.

The ResNet50 network is a convolutional neural network designed for efficiency. It is composed of 50 layers and utilizes “skip” or “residual” connections. ResNet50 was developed by researchers at Microsoft and formed part of the ResNet family of architectures, which are characterized by 50 layers and “skip” or “residual” connections. ResNet50 represents a foundational convolutional neural network (CNN), serving as a reference for subsequent models. Indeed, almost all subsequent CNNs incorporate features from the ResNet architecture. The key features of ResNet are as follows:

- The model incorporates shortcut connections that skip one or more layers. The shortcuts or bypasses facilitate the fusion of information between the input and output.
- The network was designed to eliminate the vanishing gradient problem that is common in deep networks.

ResNet50 is a widely utilized network for image classification, object detection, and a range of other vision tasks [35].

The Darknet53 network is as follows: Darknet53 is a 53-layer network that serves as the foundation for YOLOv3, a widely used object detection model. It is renowned for its optimal balance of performance and efficiency. The principal characteristics of Darknet53 are as follows: This model serves as the foundation for YOLOv3, and it effectively extracts features through the use of 53 convolutional layers.

Primarily, it serves as the foundation for object detection models, such as YOLOv3, and is also utilized in YOLOv7 and YOLOv8, where similar Darknet53 architectures are employed as the backbone [36].

AlexNet is a convolutional neural network (CNN) designed by Alex Krizhevsky, Geoffrey Hinton, and Ilya Sutskever. It was instrumental in advancing deep learning for visual recognition. The AlexNet convolutional neural network (CNN) was a pioneering development in the field of deep learning for visual recognition. The AlexNet algorithmic framework incorporates several key features, including the following:

The introduction of ReLU activations and dropout was a significant advancement.

It employs a deep architectural structure comprising multiple convolutional layers. The original development of AlexNet was for image classification purposes, and it established the foundation for numerous subsequent deep learning studies and applications. The success of AlexNet provided the impetus for the development of other convolutional neural networks, which continue to employ its foundational methodologies [37].

DenseNet201 is a convolutional neural network developed by Google Brain. DenseNet201, developed by Facebook AI Research (FAIR), represents a member of the DenseNet family, distinguished by its densely connected layers. The key features of DenseNet201 are as follows:

This enables each layer to receive features from all preceding layers.

It facilitates the propagation of features while simultaneously reducing the number of parameters. DenseNet201 is a widely utilized network for image classification, segmentation and other vision tasks [38].

InceptionV3 is a convolutional neural network developed by Google researchers. It is part of the Inception family of networks, which are distinguished by their use of parallel processing through the incorporation of distinct “modules”. It is a deep and wide convolutional neural network (CNN), similar to GoogLeNet. The key features of InceptionV3 are as follows:

It employs parallel operations within each module, thereby facilitating efficient computation.

The objective was to achieve high accuracy without excessive computational demands. It is widely employed in the fields of image classification, transfer learning, and diverse image processing tasks [39].

InceptionResNetV2 represents a further development of the Inception architecture. InceptionResNetV2, developed by Google, combines the strengths of the Inception architecture with ResNet’s residual connections. However, it should be noted that this does not always guarantee superior performance over ResNet or InceptionNet. The model features the following:

It combines the parallel module processing of Inception with the residual connections of ResNet.

The design objective was to achieve high performance while maintaining computational efficiency. Similarly, as with InceptionV3, it is a prevalent tool in the domain of image classification and diverse vision tasks [40].

GoogLeNet: The GoogLeNet model features a deep and wide architecture with the following essential characteristics:

The model incorporates the Inception module, which employs parallel operations to facilitate efficient computation.

It contains a significantly reduced number of parameters in comparison to contemporary models, while maintaining the same level of accuracy. Initially designed for image classification, GoogLeNet has subsequently formed the basis for further deep vision research and applications [41].

This study proposes a next-generation hybrid deep feature-based image classification method. The principal objective of this image classification method is to illustrate the potential advantages that artificial intelligence can offer in the field of occupational health and safety. In order to achieve this, the proposed model was applied to a helmet dataset. The principal objective of this model is to facilitate the automatic and highly accurate

detection of helmets. The proposed model comprises four principal phases, which are outlined below:

The model comprises the following stages:

- Feature extraction;
- Feature selection;
- Classification;
- Weighted voting.

A block diagram of the proposed model is provided in Figure 2 for the purposes of clarity.

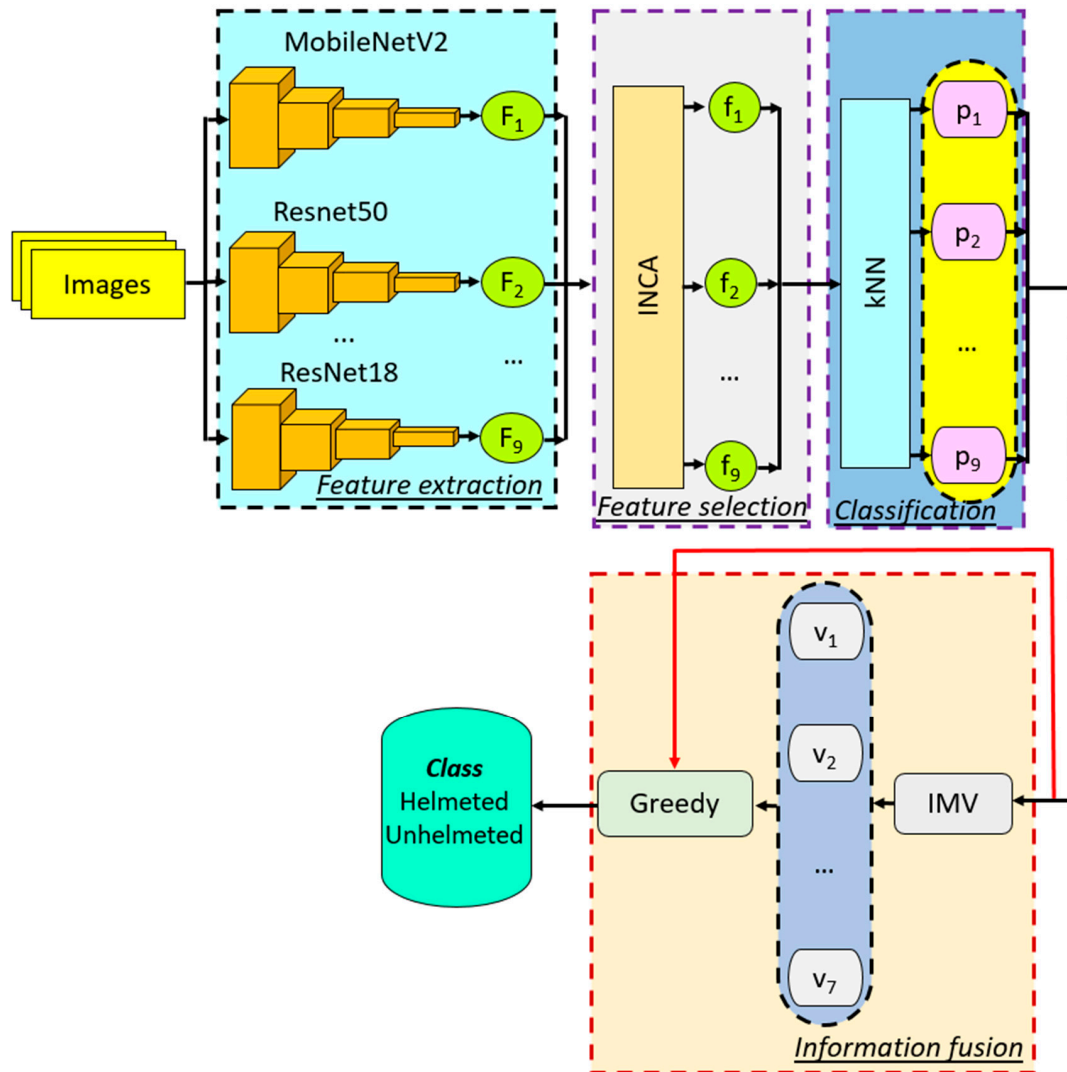


Figure 2. Block diagram of the proposed helmet recognition model. The abbreviations in this figure are as follows: F: feature vectors obtained from pre-trained CNNs, INCA: iterative neighborhood component analysis, f: selected feature vectors, kNN: k-nearest neighbor, p: outputs obtained from classifiers, IMV: iterative majority voting, v: weighted voting outputs. In this model, nine feature vectors were extracted from pre-trained CNNs, and these pre-trained CNNs were trained on ImageNet1k, and the most informative features of these features have been extracted by deploying the INCA feature selector; this feature selector is a self-organized feature selector. In the classification phase, by deploying the kNN classifier, nine classification outcomes were generated, and the generated nine kNN-based classification outcomes were utilized as input for the IMV. IMV created more than seven classification outputs. In the last phase, the best out of the 16 created (=9 kNN-based + 7 voted) outcomes were selected by deploying a greedy algorithm. The greedy algorithm selects the outcome with the maximum classification accuracy.

As shown in Figure 2, the proposed model generates nine feature vectors, each of length 1000, using nine pre-trained CNNs. The pre-trained CNNs used to create these feature vectors are the following: (1) MobileNetV2, (2) ResNet50, (3) DarkNet53, (4) AlexNet, (5) DarkNet19, (6) DenseNet201, (7) InceptionV3, (8) InceptionResNetV2, and (9) ResNet18. The iterative neighborhood component analysis (INCA) technique is applied to these feature vectors to select the most significant features. These selected features are then fed into the kNN classifier, producing nine classifier-based outputs. These nine outputs are input into the IMV method, resulting in seven weighted outputs. Thus, the proposed model produces a total of 16 (9 + 7) outputs, from which the one with the highest performance is selected. The steps of the model's operation are described in detail below.

Step 1: The images from the dataset are loaded into the model.

Step 2: The fully connected layer of each pre-trained network is applied to each image, creating nine feature vectors, each containing 1000 features.

Step 3: INCA is applied to the extracted features to select the most meaningful ones, resulting in nine selected feature vectors.

Step 4: Each feature vector is classified using kNN classifiers, yielding nine classifier-based outputs.

Step 5: The outputs from Step 4 are input into the IMV method to obtain weighted outputs. In this phase, the reason for obtaining seven outputs from nine is that the iterative variable in the IMV method starts at three.

Step 6: The accuracy of the 16 outputs is calculated, and the output with the highest accuracy is selected as the final result by a greedy algorithm.

The proposed model was implemented using MATLAB (2023a). First, the deep networks used were loaded into the MATLAB environment. Then, the model was functionally coded using m-files to design and execute the model.

Transfer learning models are renowned for their robust classification capabilities, as evidenced by their deployment in large language models (LLMs). In light of the aforementioned considerations, a deep feature architecture based on transfer learning has been put forth [42]. In contrast to end-to-end learning models, transfer learning models do not necessitate the use of dedicated hardware. This is because, in contrast to end-to-end learning models, transfer learning models do not necessitate the adjustment of millions of parameters. As the proposed model employs transfer learning, it can readily be executed on computers with straightforward configurations and without costly hardware. Transfer learning models are renowned for their robust classification performance, as evidenced by their deployment in large language models (LLMs). For these reasons, a deep feature architecture based on transfer learning has been put forth [42].

In order to evaluate the model, the most commonly used performance metrics, namely accuracy and balanced accuracy, were employed. The aforementioned metrics were calculated using the values of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) instances. The representation of these values in the error matrix is illustrated in Figure 3.

Based on the analytical structure in Figure 3, Equation (1) for accuracy and Equation (2) for balanced accuracy are given as follows [43,44].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Balanced\ accuracy = \frac{\frac{TP}{TP+FN} + \frac{TN}{TN+FP}}{2} \quad (2)$$

The model's performance was evaluated based on the assessment criteria outlined in the following section.

		Predicted Class	
		Helmeted	Unhelmeted
Actual Class	Helmeted	TP	FN
	Unhelmeted	FP	TN

Figure 3. The confusion matrix used to compute the classification performances. Herein, we have used the helmeted class as a positive class and the unhelmeted class as a negative class. By using the depicted parameters, the classification performances have been computed. Green for true and orange for false classifications.

3. Results and Discussion

The proposed model was evaluated in terms of its accuracy and balanced accuracy metrics. Additionally, the outcomes of the feature selection process and the classification results based on the convolutional neural network (CNN) architectures employed are provided in detail, offering insights into the model's effectiveness.

The proposed model initially extracted nine feature vectors, each comprising 1000 features. Subsequently, INCA was employed to identify the most efficacious features for addressing the issue. The number of selected features in accordance with the CNNs utilized is illustrated in Figure 4.

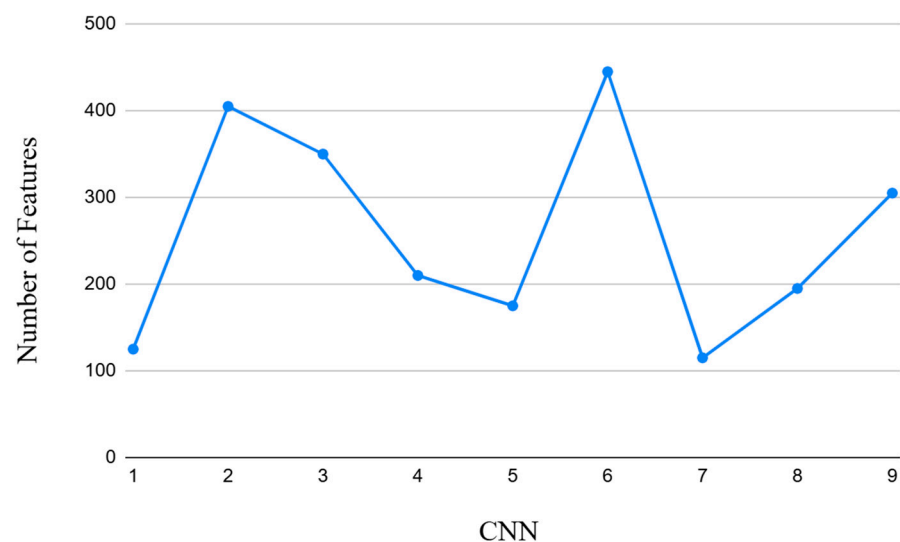


Figure 4. Number of features selected by INCA for each CNN used.

The convolutional neural networks (CNNs) corresponding to the numbers on the x -axis are as follows: the CNNs are ordered from 1 to 9, with 1 corresponding to MobileNetV2, 2 to ResNet50, 3 to DarkNet53, 4 to AlexNet, 5 to ShuffleNet, 6 to DenseNet201, 7 to InceptionV3, 8 to InceptionResNetV2, and 9 to GoogLeNet.

As illustrated in Figure 4, INCA selected a distinct number of features for each feature set, resulting in feature vectors of varying dimensions for each CNN. INCA selected the top 105 features from the feature vector generated by DarkNet53, whereas it selected 573 features for ResNet18. As previously stated, the proposed model produces 16 results, categorized into two distinct groups: weighted and classifier-based. The results are presented in Tables 1 and 2 for the reader's convenience.

Table 1. Classifier-based results (%).

No	Method	Accuracy	Balanced Accuracy
1	MobileNetV2 + INCA + kNN	87.57	87.62
2	ResNet50 + INCA + kNN	86.71	86.74
3	DarkNet53 + INCA + kNN	86.92	86.97
4	AlexNet + INCA + kNN	84.90	84.96
5	DarkNet19 + INCA + kNN	86.49	86.54
6	DenseNet201 + INCA + kNN	88.37	88.46
7	InceptionV3 + INCA + kNN	86.49	86.57
8	InceptionResNetV2 + INCA + kNN	87.43	87.44
9	ResNet18 + INCA + kNN	85.33	85.26

Table 2. Results of weighted vectors (%).

No	Accuracy	Balanced Accuracy
1	90.10	90.21
2	89.23	89.47
3	90.17	90.29
4	90.17	90.37
5	89.81	89.94
6	89.88	90.07
7	90.39	90.53

As illustrated in Table 1, the kNN results indicate that DenseNet201 yielded the most optimal outcomes, with an accuracy of 88.37% and a balanced accuracy of 88.46%. The aforementioned outputs were then employed as inputs for IMV, with the objective of calculating the weighted results which are presented in Table 2.

As demonstrated in Tables 1 and 2, the highest accuracy and balanced accuracy rates were calculated to be 90.39% and 90.59%, respectively. These results exceed the 86.28% accuracy rate reported by Özüağ and Ertuğrul (2022) [10], which encompassed a diverse range of work environments, including construction. In comparison to other safety helmet detection methods, such as the EGS-YOLO model developed by Han et al. (2024) [45], our study presents a distinct approach tailored to the specific context of agricultural machinery factories. While both studies share the common objective of enhancing occupational safety through the detection of helmet usage, the focus, methodologies, and application environments differ significantly. The EGS-YOLO study emphasizes real-time performance improvements for dynamic environments like construction sites. By modifying YOLOv7 through the introduction of GhostModule, SE blocks, and the EIOU loss function, the model achieved a mAP of 91.1% with a 13.3% reduction in inference time compared to YOLOv7. This makes the EGS-YOLO method highly effective for real-time detection, where speed and computational efficiency are paramount. In contrast, our approach employs transfer learning with nine pre-trained neural networks, combined with iterative neighborhood component analysis (INCA) for feature selection and k-nearest neighbor (kNN) classification. By utilizing iterative majority voting (IMV) across multiple networks, our model prioritizes accuracy, achieving 90.39%, with DenseNet201 yielding the best performance. While real-time detection is not the primary focus, the model demonstrates significant potential in controlled environments, such as agricultural machinery factories,

where high accuracy is critical for enhancing occupational safety. Thus, the two approaches complement each other in terms of application: the EGS-YOLO model is more suited for real-time monitoring in fast-paced environments like construction sites, while our model provides a robust solution for accurate detection in more controlled, factory-based settings. Both models contribute valuable insights to the field of AI-driven helmet detection, addressing different safety requirements based on the specific operational context. The confusion matrix for the results is presented in Figure 5.

		Predicted Class	
		Helmeted	Unhelmeted
Actual Class	Helmeted	620	42
	Unhelmeted	91	631

Figure 5. Confusion matrix of the proposed model. Herein, there are 620 true helmeted, 42 false unhelmeted, 91 false helmeted, and 631 true unhelmeted predictions where helmeted positive and unhelmeted define negative classes. Green for true and orange for false classifications.

The proposed AI-based helmet detection model comprises a model designed to ascertain the status of helmet-wearing among individuals engaged in work activities within tractor factories. The dataset employed for model evaluation comprises images of individuals with and without helmets. The model commences with the derivation of feature vectors from nine distinct pre-trained neural networks, followed by the identification of the most salient features through the application of iterative neighborhood component analysis (INCA). Subsequently, the selected feature vectors are classified using the kNN method, thereby generating the results. Subsequently, these results are combined using the IMV algorithm in order to achieve the highest possible performance. The proposed model exhibited an accuracy rate of 90.39% on the collected dataset. The application of INCA for feature selection is a unique approach that is not widely documented in the existing safety helmet detection literature. For example, the EGS-YOLO model [45] focuses on the real-time detection of helmets using modified YOLO architecture but does not incorporate feature selection methods like INCA, which could potentially increase its accuracy in complex backgrounds. The results of this study show a noticeable improvement over similar models discussed in the literature. The model developed by Liang and Seo [46] achieves a mean average precision (mAP) of 92.87% for helmet detection using UAV imagery, which is slightly higher than our top accuracy rate. However, our model operates under different environmental conditions where UAV-based imaging is not feasible, demonstrating its utility in stationary, indoor settings where different types of agricultural machinery operate. The current study extends the functionality of typical CNN-based models by integrating feature selection directly into the classification pipeline, which is a significant enhancement over models such as those discussed by Campero-Jurado et al., where the focus is primarily on integrating different AI models without optimizing feature selection [21]. Our approach not only identifies the most relevant features but also reduces computational overhead, making it suitable for real-time applications where processing power is limited.

The adaptation of CNNs with INCA for helmet detection in agricultural settings addresses several practical challenges, including variable lighting conditions, diverse backgrounds, and the non-standard positioning of workers relative to the camera. These conditions often pose problems for traditional detection systems, as noted by Hayat and Morgado-Dias [19], whose YOLO-based system excels in structured environments like construction sites but might underperform in less controlled situations.

This study primarily utilized features extracted from nine pre-trained models, followed by iterative neighborhood component analysis (INCA) for feature selection and kNN for classification. While the primary focus was on achieving optimal performance through ensemble methods, a detailed comparison of the individual performance of these neural networks could provide deeper insights into their effectiveness for helmet feature extraction. Such an analysis could identify which networks perform best under specific conditions or dataset characteristics. This represents a valuable direction for future research, potentially enhancing the model's applicability across diverse industrial environments.

4. Conclusions

This study examined an artificial intelligence (AI)-based helmet detection model developed to enhance safety practices in tractor factories and agricultural machinery manufacturing facilities. The objective of the proposed model is to reliably ascertain the status of helmet-wearing among employees through the integration of image processing and machine-learning techniques.

The proposed AI-based model offers a number of significant advantages. A number of these advantages are outlined below:

- The model exhibits a high level of accuracy, with a rate of 90.39%, which demonstrates its capacity to reliably detect helmet-wearing status, a crucial aspect for ensuring safety in tractor factories.
- The model's capacity to perform deep feature extraction is enabled by the integration of nine distinct pre-trained neural networks, thereby facilitating the capture of more intricate features and the generation of more precise outcomes.
- The application of explainable AI techniques facilitates a more comprehensive understanding of the model's decision-making process, enabling occupational health and safety experts to comprehend the rationale behind the model's conclusions.

It is important to consider the limitations of the proposed model.

- One potential limitation is the model's ability to generalize, which may be affected if it has not been tested under varying conditions, such as different lighting, image angles, and individual types.
- The utilization of the model is contingent upon the availability of a sufficient and representative dataset. An imbalanced class distribution or an insufficient number of samples may have an adverse effect on the model's performance.
- It is important to note that the computational power and time required to train and run the model may be constrained in certain cases, which is particularly pertinent for real-time applications.

It is recommended that further research be conducted in the following areas:

Although the proposed model represents a substantial advance in the field of safety practices in tractor factories, further research is required in several areas.

- To enhance the generalizability of the findings, it would be beneficial to utilize larger and more diverse datasets from a greater number of tractor factories.
- It would be beneficial to investigate the model's performance under a range of conditions, including different lighting, image angles, and individual types.
- The model's real-time applicability and performance could be optimized to facilitate the instantaneous monitoring of helmet-wearing status.
- It is possible that similar models could be applied to safety practices in other industries, thereby providing potential for further research in this area.

The steps represent prospective avenues for further development, with the objective of augmenting the impact of the AI-based helmet detection model on occupational safety.

In conclusion, this study presented an AI-based helmet detection model, which represents a significant advancement in the enhancement of workplace safety in facilities engaged in the production of tractors and agricultural machinery. It is anticipated that this model will provide valuable assistance to safety professionals and enhance worker safety. It is recommended that this model be employed in conjunction with other safety measures, taking into account a range of factors to guarantee a secure and safe working environment.

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