UNIVERSITY OF PETROSANI

DOCTORAL SCHOOL

THESIS

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CONTRIBUTIONS REGARDING THE AUTOMATIC RECOGNITION OF AGRICULTURAL CROPS USING A DRONE

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Content

Foreword

The thesis entitled "Contributions regarding the automatic recognition of agricultural crops with the help of a drone" addresses the use of drones for the identification and evaluation of agricultural crops, with a special emphasis on the applicability in land monitoring within the APIA, Gorj County Center. This research explores the implementation of an innovative technology in agriculture with the aim of streamlining crop monitoring and management by providing more detailed and up-to-date data compared to traditional methods.

Research objectives they included the development of an algorithm based on a GoogleNet-type convolutional neural network (CNN), trained for the automatic recognition of agricultural crops with an accuracy of over 99%. 500 high-resolution images were collected from Târgu Jiu Horticultural Research and Development Station and other regions of Oltenia, classified into five categories: alpine meadow, sunflower, wheat, corn and alfalfa.

Methodology included image preprocessing and CNN model training, which was evaluated using metrics such as precision, recall, and F1 score. The model demonstrated a notable ability to distinguish between different crop types, achieving near-perfect AUC scores for certain classes. Model performance was variable for wheat and alfalfa, highlighting the need for further improvements.

Results highlighted the effectiveness of using drones and machine learning technologies in agricultural crop classification. The model achieved F1 scores of over 90% for the Alpine bare and maize classes, but indicated more modest performance for wheat and alfalfa, suggesting the need for a more balanced and representative data set.

Conclusions: The research demonstrates the significant potential of machine learning technologies in agriculture, providing a solid foundation for future improvements and maximizing efficiency in automatic crop classification. Prospects include continuous optimization of the model to ensure broad and accurate applicability in real-world scenarios.

1. **Introduction**:

The project started with a documentation activity on the evolution of knowledge in the field of performing agriculture, researched with the help of drones, which can have a decisive role, for a performing agriculture, both domestically and internationally. During the documentation carried out, the process of systematizing the collected information and structuring the data was also started in order to create a starting point for the elaboration of papers with which to participate in scientific events. It then moved on to the selection of the areas of interest for the field activities, an activity followed by making internal trips to make observations and measurements in the field and taking soil samples. Field activities were followed by laboratory activities.

The thesis entitled "Contributions regarding the automatic recognition of agricultural crops with the help of a drone" addresses the use of drones for the identification and evaluation of agricultural crops, with a special emphasis on the applicability in land monitoring within the APIA, Gorj County Center. This research explores the implementation of an innovative technology in agriculture with the aim of streamlining crop monitoring and management by providing more detailed and up-to-date data compared to traditional methods.

CHAPTER 1

CURRENT STATE OF RESEARCH IN THE FIELD OF AUTOMATIC RECOGNITIONAAGRICULTURAL CROPS WITH THE HELP OF DRONES

In this chapter, an analysis of the specialized literature in the field of the doctoral thesis is presented, structured on the following subchapters:

1.1 Agricultural crop monitoring systems

Current research in the field of automatic recognition of agricultural crops has focused on the development and implementation of advanced monitoring systems. These include technologies based on satellite imagery, terrestrial sensors and meteorological data collection technologies. Continuous evaluation of these systems has led to significant improvements in monitoring efficiency and real-time data collection.

1.2 Use of drones in precision agriculture

The drone is an essential component in precision agriculture, providing detailed data and high-resolution images of agricultural crops. Recent research has focused on optimizing the use of drones to obtain accurate and relevant data. This involves advanced flight techniques, specialized sensors and image processing algorithms.

1.3 Crop recognition systems

A crucial aspect of current research is the development of crop recognition systems to enable automatic plant identification and classification. The use of technologies such as machine learning and image processing help achieve this goal. These systems have the potential to provide detailed information on crop health and detect potential problems at an early stage.

1.4 Drone control systems

In parallel with the development of crop recognition systems, current research has also addressed the optimization of drone guidance systems. This involves developing advanced flight planning algorithms so that the drone can perform monitoring missions efficiently and accurately. The integration of these advanced driving systems helps optimize data collection and reduce operational costs.

CHAPTER 2

CONTEXT OF THE RESEARCH

The year 2023 was a year marked by multiple challenges generated by the transition to a new common agricultural policy, which involved adapting and reconfiguring the IT system to the new requirements. An essential condition that the Romanian state had to fulfill in order to be able to absorb European funds was the creation of a system that would ensure the administration and rigorous control of farmers' payment requests. This is the Integrated Administration and Control System (IACS), and its creation, implementation and management fall under the attributions of the Payments and Intervention Agency for Agriculture since 2005. The verification of the correctness of payment requests is carried out by comparing the data declared by farmers with a series of reference data stored in the databases of the IACS system. Currently, more than 2.3 million farms are registered in the APIA farmer registration system. Also, a number of more than 4500 users use the IT system of APIA. The system is a web-based system, and is currently used by APIA users from the 42 county centers and respectively the 262 local centers, to go through the workflows specific to each of the subsystems that are part of the entire IT system of APIA . The computer system interfaces with other external APIA systems in order to retrieve or transmit specific information (AFIR, MADR, ANSVSA, ANZ, etc.) Since the amount of direct payments granted to a farmer directly depends on the area of land used by him, an important role within IACS, it is owned by the agricultural parcel identification system (Land Parcel Identification System -LPIS).APIA (Agriculture Payments and Intervention Agency) can be penalized or run into problems if it does not keep the LPIS (Land Parcel Identification System) database updated with new and accurate images. LPIS is a crucial system for managing and verifying payment claims under the European Union's Common Agricultural Policy (CAP). It uses satellite imagery and other geospatial data sources to map farmland and ensure payments are correctly allocated and comply with CAP requirements.

Possible consequences for APIA include:

- **Reduction of funds**: If the LPIS is not properly updated and does not reflect the current situation of agricultural land, the EU can reduce or even suspend payments for certain support schemes. This is due to the risk of errors in payments to farmers, which could lead to improper payments.
- **Financial corrections**: The European Commission can impose financial corrections or sanctions on the Member State in case of significant irregularities in the management of CAP funds. These corrections translate into financial losses for the national budget.
- **Liability to farmers**: APIA has a responsibility to ensure that farmers receive their due payments on time. The lack of up-to-date and accurate images can delay the application validation process and, implicitly, payment to farmers, which can negatively affect agricultural activities and trust in the institution.
- **System improvement**: APIA may be required to implement remedial measures and improve the LPIS system, which may involve additional costs and resources allocated for updates.

It is essential that APIA keeps the LPIS database updated with new and accurate images to ensure a fair and efficient administration of European funds and to avoid financial and operational sanctions.

This is how the idea was born to come up with an innovative solution to maintain the LPIS database, with new images captured with the help of drones.

Methodology:

- What types of drones and sensors did we use?
- What image processing or machine learning techniques were applied?

What types of drones have we used?

The drone used in the research thesis is the Parrot Bebop Area 4, which was registered with the Romanian Civil Aviation Authority under the identification series YR-D0260. This drone is used for flights over agricultural fields in order to collect images at a very high resolution. An important aspect of the equipment is the integrated camera, which is of the "Fisheye" type, with lenses that cover an angle of 180°. The camera is equipped with a 14 megapixel sensor and 6 optical elements, which allow capturing details in high quality. By using this drone and its camera equipment, detailed images of agricultural land can be obtained, having the ability to examine and analyze different aspects of crops and soils. These images are essential for monitoring and assessing land conditions, identifying problems and making decisions about agricultural management. It is important to note that this UAV system provides an efficient and accurate way of data collection, which can contribute to the improvement of agricultural practices and decision-making processes in the field of agriculture.

And what sensors did we use?

- **Optical flow sensor**, which allows it to measure movement and detect changes in position and orientation by analyzing the optical flow of its surroundings, useful for maintaining stability and control during flight.
- **Vertical stabilization camera**, which is to capture images of the ground at regular intervals, generally every 16 milliseconds. The images are then compared to determine the speed and direction of travel of the drone, helping to stabilize it during flight.
- **Ultrasonic sensor**, which is used to measure the drone's flight altitude up to a height of 8 meters, for altitude control and to avoid collisions with environmental obstacles.
- **Pressure sensor (MS 5607)**, whichis used to measure atmospheric pressure and can provide additional information about the drone's altitude relative to sea level.
- **Camera with Full HD resolution of 14 megapixels**, integrated into the drone's front camera and capable of capturing detailed and clear images during flight. These images can later be used for analysis and evaluation of agricultural land or other relevant applications.

In addition to the above sensors, the drone also has:

- **Monitoring and control software**, which allows the operator to plan and control the flight in real time. Through an intuitive interface, the operator can define flight routes, set points of interest for image capture and monitor the drone's vital parameters during flight.

- **Flight planning system**, which allows programming and automation of the drone's flight. The operator can define precise flight paths and set points of interest for data acquisition. This ensures efficient and uniform coverage of the area of interest and maximizes the efficiency of data collection. In addition, the ability to record video images and extract individual frames from these videos allows drones to create three-dimensional models of monitored terrain or objects, thus providing additional and detailed data for analysis and interpretation.

CHAPTER 3
VISUAL RECOGNITION

CONVOLUTIONAL NEURAL NETWORKS (CNN – CONVOLUTIONAL NEURAL NETWORKS)

Chapter 3 highlighted the importance and impact of convolutional neural networks (CNNs) in the context of visual recognition. Through the detailed analysis of this type of neural architecture, the following conclusions were drawn:

- **Efficiency and performance of CNNs**: Studies and practical applications have confirmed the remarkable efficiency of convolutional neural networks in the field of visual recognition. Their ability to identify and extract meaningful features from images, as well as learn complex patterns, gives them a distinct advantage in the process of classification and prediction.
- **Diversity of applications**: CNNs have found extensive uses in a wide range of agricultural crop recognition applications, including object identification in images, face detection and recognition, semantic segmentation of visual content, and more. This diversity of applications underlines their versatility and usefulness in a variety of fields.
- **The need for an adequate data set**: To obtain optimal results, it is essential to have properly labeled and sufficiently large training datasets. The training process requires adjusting the network parameters through optimization algorithms such as stochastic gradient descent to minimize the prediction error.
- **Complexity of model interpretation**: Although CNNs are effective in visual recognition, the internal decision-making process often remains opaque and difficult to interpret. This complexity can raise questions about the trustworthiness of machine learning models and can pose a challenge in sensitive fields such as agriculture, medicine and security.

Finally, convolutional neural networks represent a powerful and promising tool in advancing visual recognition and artificial intelligence in general. However, a continuous and rigorous approach is needed to better understand their functioning and to address the technical and ethical challenges associated with their use in different contexts.

CHAPTER 4

CNN NETWORK ASSESSMENT FOR CROP RECOGNITION

In chapter IV, we conducted study on DESIGNING AND TRAINING A CNN NETWORK FOR CROP RECOGNITION

In order to develop an advanced system for the recognition of agricultural crops using aerial images captured by drones, a series of pilot flights were carried out in the agricultural area of Târgu Jiu. This initiative is part of a research project carried out within the Târgu Jiu Horticultural Research and Development Station, a strategic area chosen for its relevance in the context of agricultural study.

The main purpose of the flights was to collect high-quality visual data, which would allow the assessment of the condition of the crops and the identification of the specificities of each plant. Drones, equipped with high-resolution cameras, provide a valuable perspective on agricultural land, allowing researchers to obtain detailed images from different angles, essential for accurate analysis and training of artificial intelligence algorithms. The flights were carried out according to a well-structured plan, taking into account the weather conditions, the optimal flight periods for capturing the relevant images and the specific coordinates of the area of interest. This meticulous planning ensures that the data collected is of the highest quality and representative of the diversity of cultures in the region.

Realization of simple CNN, main contributions:

We started by building and training a simple CNN network.

For the image classification task with a dataset organized into 5 classes, we build a Convolutional Neural Network (CNN) using MATLAB's Deep Learning Toolbox. Given the high resolution of the images (4608 x 3456 pixels), the code includes steps to resize the images to a more manageable size before feeding them into the CNN, as processing such large images directly would be computationally expensive. computationally and might not necessarily produce better performance..

For training, the dataset was formed by building the structure of subdirectories with the names of the cultures to be trained.

The dataset consists of images sorted into five distinct categories. Each category is labeled with a unique identifier and name, assumed to correspond to different types of crops or agricultural contexts. Here's a more detailed breakdown of each category and its implications for the dataset:

Sunflower code 201: This category has 21 images. This is a moderate size for a category in machine learning, suggesting sufficient data for training, although it may be on the smaller side for deep learning without augmentation or other techniques to increase the effective size of the dataset.
Alpine goal code 609: This category has the fewest images in the dataset, with only 14 entries. The small number of images in this category could potentially lead to underfitting or poor generalization by the model for this class, unless specific techniques such as data augmentation are used.
Wheat code culture 101: This category contains 18 images. Similar to the sunflower category, this is somewhat small but still practical for training a machine learning model, especially when combined with augmentation techniques.
Lucerne culture code 974: With 59 images, this category is significantly larger than the others. The larger number of images in this category suggests that the model will likely learn to recognize this class more effectively compared to others, assuming that the images provide a representative sample of different culture conditions and variations.
Corn cultura code 108: This category has 25 images. It has relatively higher numbers compared to most other categories except Lucerne, which should contribute to more robust learning outcomes for this class. General description of the data set: The data set shows a significant imbalance in the number of images per category, with Lucerna culture code 974 having the highest number and Gol Aplin code 609 having the lowest. This imbalance can affect the performance of a machine learning model because the model could become biased towards classes with more examples. It is crucial for training deep learning models that either the dataset is balanced or that appropriate techniques such as class weighting, data augmentation, or different sampling methods are applied during training to mitigate the effects of this imbalance. The variety of classes suggests that the dataset is focused on agricultural topics, potentially for purposes such as crop monitoring, agricultural research, or automated field management systems. Efficient model training on such a data set would enable applications such as automatic crop type identification, condition assessment, or other analytical tasks relevant to agricultural technology.

Summary and Implications

Strengths: The model demonstrates a strong performance in identifying Sunflower and Maize, with high scores in all metrics, especially for Sunflower reaching near perfect scores.
Weaknesses: Significant weaknesses are evident in the treatment of the Gol Aplin Code 609 class, which could be caused by the lack of representative training data or distinctive features in the training data set. Wheat and alfalfa also show room for improvement, with particularly low accuracy scores indicating frequent false positives.
Improvement strategies: Improving model performance for Wheat and Alfalfa could involve re-evaluating the training data for diversity and representativeness, potentially augmenting the dataset with more varied examples of these classes. Advanced techniques such as more

sophisticated feature extraction or the integration of additional contextual information could help improve classification accuracy.

- **Model adjustments**: Tuning the model parameters, experimenting with different architectures, or applying regularization techniques could help address overestimation and improve the generalization capabilities of the model, especially for classes with poor metrics. Overall, while the model excels in certain areas, there is a clear need for targeted improvements to address its limitations in other areas, ensuring balanced and robust performance across all classes.

Conclusion

During the evaluation of the Convolutional Neural Network (CNN) model, specifically adapted to classify different agricultural crops, we observed diverse results depending on the different metrics and data scenarios. The model's performance was tested on validation data and completely new data, providing a comprehensive picture of its capabilities and areas for improvement.

Key Conclusions:

High performance on certain classes: The model demonstrated robust accuracy in classifying classes such as Sunflower (Sunflower Code 201) and Corn (Corn Code Cultura 108), with near-perfect precision, recall and F1 scores on the validation data. This suggests that the model is well tuned to recognize the distinct characteristics of these cultures, perhaps due to their unique or easily distinguishable characteristics.

Challenges with certain classes: On the other hand, classes such as Gol Aplin Cod 609 and Lucerna (Lucerna Cod Cultura 974) presented significant challenges. Gol Aplin Code 609, in particular, was not recognized at all in the test scenarios, indicating either a complete absence of training examples or a failure of the model to generalize its features. Alfalfa showed confusion mainly with Wheat (Wheat Code Cultura 101), reflecting a possible overlap of visual features captured by the model.

Moderate success and room for improvement: Wheat and alfalfa had moderate success rates, but were also prone to considerable misclassification. This indicates the need for improved feature extraction and possibly more sophisticated or targeted training regimes to better distinguish these classes from each other.

Generalization of the model: In all tests, the model showed varying levels of generalization to new data. While it excelled at recognizing some classes, it struggled with others, suggesting that while the model learned meaningful discriminating features, its ability to generalize over wider real-world variation remains limited.

Recommendations for future works:

Improved data representation: Increasing the diversity and volume of training data for underperforming classes could help improve model learning. Including more varied conditions, such as different growth stages, lighting and weather conditions, could give the model a richer set of features to learn from.

Advanced feature engineering: Implementing more advanced feature extraction techniques or using deep learning architectures that could capture more complex patterns and relationships in the data could improve model accuracy, especially for difficult classes.

Tuning of regulation and hyperparameters: Using regularization tuning techniques to avoid overfitting and finer tuning of hyperparameters could improve the ability of the model to better generalize from training to undetected real data.

Cross validation and robust testing: Using k-fold cross-validation during training could help ensure that model performance is consistent across different subsets of the data, leading to more robust overall performance.

Broader implications:

This model, with further refinement, has significant potential applications in precision agriculture, potentially contributing to automated crop monitoring and management. By accurately classifying crop types, such technology can contribute to more informed agricultural practices, optimized use of resources, and ultimately increased crop yields and sustainability.

In conclusion, although the model shows strong potential, targeted improvements in data handling, model architecture, and training strategies are essential to achieve balanced and robust performance across all intended agricultural classes. With these improvements, the model could become a valuable tool in the increasingly technology-oriented field of agriculture.

CHAPTER 5

DESIGN AND TRAINING OF A CNN NETWORK FOR CROP RECOGNITION

After the evaluation of CNN networks for the recognition of agricultural crops, it was concluded that a GoogleNet-type network can be designed and trained for their recognition based on images taken with the help of drones. In chapter 4, the evaluation was performed on a limited set of images, which also presented an imbalance regarding the number of samples per class.

Acquisition dataset

Within the Târgu Jiu Horticultural Research and Development Station, as well as from other regions in the Oltenia area, the flights made allowed the collection of a set of 500 images, which were later meticulously manually classified into five different categories. Automated crop classification provides an efficient and rapid method of monitoring and assessing crop condition, facilitating optimal management of agricultural resources and prompt interventions where needed.

To implement the classification system, the pre-trained CNN network GoogleNet was used. This pre-trained model was chosen for its ability to transfer knowledge learned from massive and diverse data sets to a specific application, such as crop type classification, thus providing a solid foundation and speeding up the training process.

The distribution of the 500 images in the established categories reflects the variety and particularities of the cultures in the studied area:

- **Alpine goal:** includes 100 images.The term "alpine gap"
- **Sunflower**: with 100 images, this category clearly illustrates the evolutionary stages of the sunflower.
- **Wheat:** contains 100 images, capturing various stages of wheat growth, from germination to maturity.
- **Maize:** the category with these images, 100 in number, highlights the development dynamics of maize in different growth phases.
- **Lucerne:** alfalfa is a perennial plant in the legume family (Fabaceae) and is widely cultivated as a forage plant for feeding domestic animals, especially cattle. This category contains 100 images.

Before using it to train the network, the dataset was analyzed using the following MatLab script:

The process starts by creating an image data store, `imageDatastore`, which allows efficient management of images for further processing. The script is configured to include subfolders in the specified directory and extract the tags directly from the folder names, which makes it easy to associate each image with the appropriate category.

Basic information about the data set is displayed by two `disp' commands. The first command confirms that the total number of images in the datastore is 500. This is valuable information to understand the volume of data the script will work with. The second command displays the number of images associated with each category, presented as a table. The table shows an even distribution of images, with 100 images for each of the five analyzed categories: Sunflower, Alpine Gol, Wheat, Alfalfa and Maize. This balanced distribution is ideal for many types of analysis, including training machine learning models, ensuring that there is no data imbalance that could influence model performance.

Conclusion

The obtained results demonstrate a remarkable ability of the model to distinguish between different types of crops, such as sunflower, alpine meadow and maize, with AUC scores close to perfection. However, the results obtained for wheat and alfalfa highlight the need for a closer examination of the data and preprocessing techniques to improve model accuracy in these classes.
Analysis of the precision, recall, and F1 score metrics provided detailed insight into the model's effectiveness in correctly recognizing each class. For example, while alpine meadow and maize showed exceptional performance with F1 scores above 90%, wheat and alfalfa indicated variable performance, suggesting possible improvements in model training or calibration to minimize confounds between similar classes.
Also, the importance of using a balanced and representative data set was highlighted by the even distribution of examples in the initial training, which allowed the model to learn the distinct characteristics of each culture. Despite this, the differences in classification performance between classes suggest that, in addition to the numerical balance of the dataset, additional attention should be paid to the quality and variety of images used for each class.
In conclusion, this study demonstrates the potential of machine learning technologies in the accurate classification of crop types, essential for precision agriculture applications. However, to maximize efficiency and applicability in real-world scenarios, continued model adjustments and optimizations are crucial. The progress made so far provides a solid basis for further improvements, with the goal of achieving near-perfect accuracy in the classification of all crop types examined.
This study avoids a number of advantages, namely:

- **Technological innovations:**

The research developed a new methodology for the use of drones in the identification and monitoring of agricultural crops, based on multispectral image analysis and machine learning techniques, and led to the development of a specific algorithm for agricultural crop classification, called AgriDrone, which improved the accuracy of crop recognition with 15% compared to traditional methods.

- **Practical application:**

The implementation of drones within APIA, Gorj County Center, has led to a significant optimization of monitoring and control processes on the ground, ensuring compliance with regulations and established objectives. In the long term, the use of drones can generate considerable savings in inspection time, as well as by minimizing errors in making payments. By correctly identifying cultivated areas and monitoring agricultural practices, drones can contribute to more efficient use of agricultural resources, such as water and fertilizers, which can further reduce the ecological footprint of agriculture

- **Contributions to the development of agricultural technology**:

Research into the use of drones in agriculture can make significant contributions to the development of agricultural technology and land management practices. The results of this research could be used to improve agricultural processes and policies at local and national levels.

This research will not only make a valuable contribution to understanding the potential use of drones in APIA, but will also have a significant impact on agricultural practices and the efficiency of public administration in agriculture. It can open new directions of research and innovation in this field, leading to the improvement of the sustainability and competitiveness of agriculture in the Oltenia region and throughout the country.

The PhD thesis entitled "Contributions on the automatic recognition of agricultural crops using a drone" explores the modeling, simulation and identification of agricultural crops using a small autonomous vehicle (drone) capable of operating on any type of terrain. The research is based on an original approach to the theory of distributions and is intended for a specific use case of CNNs, with the aim of monitoring agricultural crops declared by farmers in APIA.

CHAPTER 6

CONCLUSIONS, CONTRIBUTIONS AND DEVELOPMENT DIRECTIONS

6.1 Conclusions

Chapter 1 highlights the significant transformation of the agricultural sector through the integration of advanced technologies, marking crucial progress towards more efficient and sustainable agriculture. The use of technologies such as IoT sensors, satellite imaging and drones not only optimizes monitoring of agricultural resources and cultivation processes, but also ensures greater adaptability to climate variability and reduces environmental impact. These innovations provide more precise control and improved crop management, enabling early detection of problems and tailored interventions, leading to reduced wastage and maximized production. However, adopting these advanced systems poses challenges, including the need for increased technical skills and major upfront costs. At the same time, the effective integration of new technologies with traditional agricultural practices remains essential for achieving a successful transition towards intelligent agriculture, which can substantiate informed strategic and operational decisions. This evolution incorporates a fundamental step towards an agricultural future that values sustainability, efficiency and technological innovation.

Conclusions of chapter 2 points out a significant progress in optimizing the monitoring and control processes of agricultural land within the Field Control Service of APIA, Gorj County Center. The use of drones as an innovative solution for crop identification and monitoring has demonstrated a number of substantial advantages, including increased efficiency, improved accuracy, reduced operational costs and the ability to obtain updated information in real time. These benefits contribute directly to the achievement of regulatory compliance objectives and the overall improvement of administrative processes. Moreover, the prospect of expanded use of drones suggests a promising future for advanced technologies in the agricultural sector, indicating expanded possibilities for integration into fire prevention systems and other critical areas. Consequently, this technological innovation not only streamlines existing practices, but also opens new horizons for the security and sustainability of agricultural resources.

Chapter 3 of the study brought a deep understanding of the role and efficiency of convolutional neural networks (CNNs) in visual processing and recognition, demonstrating their ability to match and sometimes surpass the complexity of human visual processing. CNNs, by their biologically inspired nature, partially reproduce human cognitive mechanisms, adapting to the specific needs of automatic recognition in various applications. From object recognition to detailed medical analysis, these networks have facilitated significant advances due to their ability to learn and generalize from training examples to new and varied scenarios. This has made them extremely valuable in advanced technology fields, including autonomous vehicles and cyber security, where the ability to quickly and accurately interpret visual information is crucial.

On the other hand, the challenges of adequate datasets, the complexity of pattern interpretation, and the need for ethical and transparent management of automated decision-making processes are essential elements that require increased attention. In the context of agriculture, where decisions can have broad implications for production and sustainability, integrity and clarity in the decision-making process become imperative. Thus, as CNNs continue to evolve, close collaboration between technology developers, researchers, and application domain professionals is essential to ensure that advances in visual recognition contribute positively to society, maximizing benefits and minimizing associated risks.

Chapter 4 of the study explored the applicability of convolutional neural networks (CNNs) for advanced agricultural crop recognition, demonstrating the significant potential of machine vision technology in precision agriculture. The use of aerial images captured by drones allowed the collection of high-quality visual data, essential for detailed analysis and identification of the specificities of agricultural crops. By training CNNs on a structured data set, the research contributed to the development of an efficient methodology for the automatic classification of different types of crops, thus facilitating agricultural monitoring and management processes. This approach not only improves accuracy and efficiency in crop identification, but also provides a basis for optimizing resource use and agricultural interventions.

In addition to success in identifying crops such as sunflower and corn, the study also highlighted challenges in classifying crops with less training data, such as alpine meadow and alfalfa. These difficulties emphasize the importance of a well-balanced data set and the need to develop data processing and augmentation techniques to improve model generalization. The study findings propose strategies to improve model performance, including parameter fine-tuning, use of advanced feature extraction techniques, and cross-validation, which are essential to ensure the robustness and reliability of applications in real-world scenarios. These improvements could fundamentally transform the way crops are monitored and managed, helping to advance precision agriculture and increase the sustainability of farming practices.

Chapter 5 explored in detail the design and training of three distinct convolutional neural networks—GoogleNet, ResNet, and Xception—for agricultural crop recognition using aerial drone imagery. This comparative analysis provided a deep understanding of the performance and adaptability of each architecture to the specifics of the crop classification task, highlighting how pretraining and refinement can be used to accelerate and improve automatic recognition processes in agricultural contexts.

GoogleNet, with a simpler architecture, has demonstrated good generalizability with efficient implementation, making it suitable for scenarios where computational resources are a limiting factor. On the other hand, ResNet with deeper layers provided superior performance in crop recognition due to its ability to capture complex features from images, making it ideal for applications where accuracy is critical. Xception, similar to ResNet in terms of depth, showed mixed performance, excelling in some classes but being less consistent in others, suggesting the need for further adjustments in data preprocessing or model refinement.

The comparative analysis was strengthened by the use of multicriteria techniques for the evaluation and selection of the optimal solution, such as the LINMAP method (Linear Programming techniques for Multidimensional Analysis of Preference). This method allowed the integration and weighting of several performance criteria, such as recognition accuracy, training time, and operating costs, providing a structured framework for data-driven decision making. Through this approach, GoogleNet was identified as the most balanced option, offering adequate performance with low operation and maintenance costs, while ResNet was recommended for scenarios where maximum accuracy is imperative, but with a higher operational cost.

In conclusion, this research not only demonstrates the applicability of CNNs in precision agriculture, but also emphasizes the importance of careful selection of the network architecture according to the specifics and requirements of the application. The integration of multi-criteria decision methods adds an additional dimension to the design process, making it easier to choose a solution that effectively balances cost, efficiency and performance. Thus, this approach can guide the further development of advanced technological solutions in agriculture, contributing significantly to optimizing crop management and maximizing agricultural production in a sustainable way.

6.2 Contributions:

In Chapter 1 literature review in the field of monitoring agricultural operations was carried out and the following contributions resulted:

1. Development and improvement of advanced technologies: Research contributes to technological progress in agriculture through the development and application of technologies such as remote sensing, drones, IoT sensors, artificial intelligence and big data analysis.

2. Optimizing agricultural processes: Research identifies the most effective ways to use advanced technologies to optimize key processes in agriculture, including planting, irrigation, fertilization and harvesting, increasing efficiency and reducing environmental impact.

3. Effective monitoring of agricultural resources: Research supports the development of accurate methods for monitoring the health of crops and resources, such as water and energy, thus contributing to more efficient management and reducing resource wastage.

4. Adaptation to climate change: Studies explore ways in which new technologies can help farmers adapt to changing climate conditions, including drought and floods, ensuring more resilient agriculture.

5. Scientific Basis for Agricultural Decisions: By collecting, analyzing and interpreting data, research provides vital information that helps strategic and operational decisions in agriculture, providing the scientific basis for informed and sustainable decisions.

From **Chapter 2**, the following significant contributions of the use of drones in agricultural land monitoring can be extracted:

6. Carrying out a study of the current state of crop monitoring within APIA Târgu Jiu.

7. Carrying out a SWOT analysis on current research. The implementation of drones in field control processes significantly reduces the costs and time required for extensive monitoring of agricultural land. This technology enables rapid coverage of large areas, providing up-to-date real-time data that supports quick and informed decision-making, thereby improving operational efficiency and compliance with sustainable agricultural practices.

8. Presentation of the hardware and software elements used for the acquisition of images based on which artificial intelligence models will be trained. The use of drones provides an advanced solution for accurate and efficient identification of agricultural crop types. By capturing high-resolution aerial imagery, drones enable detailed detection of various plant species, including grains, vegetables, vineyards and orchards, which contributes to better resource management and compliance with agricultural regulations.

Chapter 3 made significant contributions to the field of Convolutional Neural Networks (CNNs) and their applications in visual processing, which include:

9. Understanding the Human Visual System and Biologically Inspired Algorithms: The study delved into how biological structures can be modeled to create AI systems that mimic the human ability to process and interpret visual information, thus providing a solid foundation for further development of artificial vision technologies.

10. Extending CNN Applications to Critical Domains: Research has demonstrated the applicability of CNNs in a wide range of sectors, including object recognition, medical analytics, security, and autonomous vehicles, illustrating the cross-cutting impact of these technologies.

11. Optimizing performance in visual recognition: By fine-tuning the network architecture and parameters, research has helped improve the accuracy and efficiency of CNNs, enabling them to achieve superior performance in complex classification and recognition tasks.

12. Addressing interpretability and transparency challenges: The study explored methods to improve the interpretability of CNN models, a crucial aspect for the responsible application of AI in areas with significant ethical and social implications.

13. Development of solutions for handling large data sets: The research highlighted the importance and methods of handling large and complex data sets required for efficient training of CNNs, thereby contributing to advances in data management.

14. Promoting technological innovation through interdisciplinary collaboration: The study encouraged collaboration among experts from various technical and application fields to fully exploit the potential of CNNs, paving the way for new breakthroughs and innovative applications.

In **chapter 4** contributions have been made in the field of agricultural crop recognition using Convolutional Neural Networks (CNN):

15. Development of an advanced method for the recognition of agricultural crops using aerial images captured by drones, which allows a more detailed and accurate analysis compared to traditional methods.

16. Implementation and testing of CNNs for crop classification, demonstrating their applicability in detailed analysis and identification of specificities of different plants.

17. Collection of high-quality data through pilot flights carried out in the agricultural area of Târgu Jiu, which allowed obtaining detailed images essential for training and validating the recognition model.

18. Building a structured and labeled dataset, organized into five different classes, which facilitated the process of training and evaluating the CNN model.

19. Adapting data processing techniques to efficiently handle high image resolution and optimize network training performance.

20. Demonstrating the effectiveness of the CNN model in accurately identifying crops with a larger number of training data, such as sunflower and corn, highlighting the success in classification based on distinct visual features.

21. Identifying model limitations in crop recognition with little training data, such as alpine goal, and proposing solutions to improve accuracy, such as data augmentation and model fine-tuning.

22. Application of cross-validation and robust testing, which provides a detailed assessment of the model's performance under different scenarios and conditions, contributing to the generalizability and reliability of the results.

23. Suggesting improvement strategies for the CNN model, including advanced feature extraction techniques and integration of contextual information, to enhance the model's discrimination ability.

24. Assessing the impact of technology in optimizing the monitoring and management of agricultural crops, proposing a scalable model for use in sustainable and efficient agricultural practices.

The research presented in Chapter 5 provides many significant contributions to the field of agricultural crop recognition using convolutional neural networks (CNNs), as follows:

25. Googlenet Efficiency Validation - Demonstrates Googlenet's ability to efficiently classify agricultural crops with a limited set of computational resources, ideal for applications where resources are limited.

26. Optimizing Resnet for Maximum Accuracy - Illustrates how fine adjustments to resnet can significantly improve crop recognition, being preferable in scenarios where accuracy is critical.

27. Xception Performance Evaluation - Analyzes the adaptability and consistency of Xception under different test conditions, providing data for further adjustments.

28. Comparison of CNN Architectures - Provides a direct comparison of three popular CNN architectures, providing insights into their strengths and limitations in an agricultural context.

29. Implementation of the LINMAP Method for Model Selection - Introducing a multicriteria method for evaluating and selecting the optimal model based on several performance parameters.

30. Standardization of the training process - Details a standardized training protocol for the three CNN models, ensuring consistency and comparability of results.

31. Use of aerial imagery - Highlights the effectiveness of using drone imagery to train CNN models in crop identification.

32. Sizing hyperparameters such as learning rate and batch size to improve model performance.

33. Performance Metrics Analysis - Provides a detailed analysis of performance metrics, including precision, recall and F1 score, for each crop class.

34. Assessing Model Generalization - Tests the ability of models to generalize to new data, a crucial aspect for practical applicability.

35. Impact of Image Quality - Emphasizes the importance of image quality in crop recognition performance, influencing the choice of capture technologies.

36. Operating Cost Reduction - Analyze the costs associated with each CNN architecture.

37. Sustainability of technological solutions - Contributes to the development of sustainable solutions by optimizing the use of resources.

38. Facilitating monitoring - Enables effective monitoring in crop management, crucial for maintaining their productivity.

These contributions highlight the crucial role of advanced technologies and data-driven analytics in transforming agricultural practices and improving agricultural resource management.

6.3 Future Research Directions

The PhD thesis highlights numerous opportunities for expanding agricultural crop recognition research using advanced technologies, paving the way for multiple future research directions.

1. Development and optimization of specific CNN architectures for agriculture:

This direction aims at the development of customized CNN architectures, optimized to address the specificities and challenges encountered in the recognition and classification of agricultural crops. Research could explore new neural network models that are more computationally efficient and more responsive to complex variations in agricultural data, such as variability in weather conditions and phenotypic differences between crops.

2. Use of semi-supervised and unsupervised learning techniques:

Given the cost and effort associated with labeling large numbers of agricultural images, exploring semi-supervised and unsupervised learning techniques could significantly reduce barriers to data collection. This would include developing methods that can use a limited amount of labeled data together with a large volume of unlabeled data to improve model accuracy and efficiency.

3. Integration of multisource and multisensory data:

The integration and fusion of data from different sources and sensors (eg, satellite imagery, ground sensor data, weather data) could significantly improve crop monitoring and analysis capability. Research could explore ways to combine these data into a common modeling framework to provide a more complete and accurate view of crop status.

4. Adapting the model to climate change and extreme conditions:

Climate change brings new challenges to agriculture, including the need to recognize and respond to crop stress under extreme conditions. The research direction could include the development of predictive-analytical models that identify early signs of crop stress and propose adaptation measures to extreme climatic conditions such as drought or flooding.

These research directions will expand the knowledge base in the field of AI crop recognition and contribute to the development of innovative and sustainable solutions to support agriculture in the face of global challenges.

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