Machine learning-driven UAV mapping for automated detection of nutritional deficiencies and diseases in wheat

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Abstract

In this paper, we developed an ML-based algorithm to classify plant state and decision-making about effective responses. The algorithm aims to detect plants that is under the lack of nutrition or damaged by diseases. The algorithm also provides UAV flight mapping to match the field points with classes of plant states. The real pictures of Triticum aestivum under normal conditions, under the lack of nutrition, and damage due to diseases, were used as the training samples for automatic visual diagnostic of plant state. Cyclic training was performed in three key scenarios. A comparison of the accuracy of the simulation experiment was done. The results of the analysis demonstrated that a long-term experiment with 1000 epochs provides the highest accuracy. The peak is found within about 20-200 epochs, and the 200th epoch, where the accuracy curve reaches and remains around 60-62 % with fluctuations of ±1 %. The results of the research also demonstrate the potential of the integration of modern technologies, including UAV, artificial intelligence (AI), and machine learning, into the agricultural field of people activity, showing the advantages of considered technologies for automatic monitoring and diagnostic of the plant and quick response to treatment actions.

Keywords

machine learning, object classification, UAV, crop monitoring, UAV-based mapping, agriculture, wheat, plant, Triticum aestivum, air navigation

1. Introduction

Agriculture in Ukraine is the key component of crop production. Grain production is a branch of crop production and is of high importance. The winter bread wheat (Triticum aestivum) ranks first among other grain crops because of its productivity value and crop capacity [1]. The crop area of winter bread wheat varies from 6,4 to 7,3 million hectares. The area under this crop is two-fifths of all crops.

Nowadays, under the conditions of intensive agricultural production, factors that significantly restrict the increase in yield capacity and gross crop yield are the plant diseases caused by various pathogens [2,3]. The plants affected by diseases vary from 15% to 70%, depending on pathogen virulence and year conditions. This is equivalent to the cost of grain from an area of 1 million hectares. The volume of affected plants can be even larger during the period of epiphytotium.

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The negative influence of the environment reduces the effectiveness of mineral nutrition [4]. These include high or low temperatures, or soil acidity and alkalinity, imbalance in nutrition, moisture deficit, overwetting, diseases, damage to plants, pesticides, and many others. As a result of a decrease in mineral nutrition effectiveness, it is observed a deterioration in

- the availability of nutrients in the soil for plants,
- the actively absorbing surface and the ability of the root system to absorb nutrients,
- chloroplast activity.

The lack of each of the nutrient elements affects the appearance of the plants.

Sometimes it can be difficult enough to determine which element is in short supply. The chemical analysis of the soil or cell juice is a rather expensive procedure. Moreover, finding a high-quality specialized laboratory can also be difficult, and the analysis takes more than one day. Therefore, the method of visual diagnostic is still relevant. For correct visual diagnostic, it is necessary to inspect the plants in the field and make a decision about the cause of the visible damage to the plant. These can be insects, diseases, mechanical influence, including hail or machinery injury, and weather phenomena such as drought or cold. Most of the damages caused by the mentioned factors are characterized by massiveness. But plants that suffer from the deficit in nutrients, as a rule, are located in a group as a “bonfire” or “spots” on the field.

The deficit of nutrients is more often revealed as characteristic symptoms, but exceptions take place. Visually, it can be seen not only as symptoms characteristic of a certain type of starvation, for example, necrosis on the leaf or change in coloration of certain organs, but also as a change in the general plant appearance. The early detection and timely response to the problem can save the crop.

Taking into account the reviewed problems, it was our motivation to consider modern technical solutions to obtain reliable and timely information about the plant state, as well as to organize the operative relevant response.

Unmanned aircraft vehicles (UAVs) have demonstrated the promising ability to perform many tasks in agriculture [5,6]. The advantages of the use of UAVs in agriculture are provided by their low cost and high efficiency, ability to be equipped with a variety of sensors and instruments, reliability, ability to perform tasks operatively and in region that is difficult to access, accuracy, friendship to environment and ecology, timesaving as well [7]. It is not the full list of advantages. The integration of UAV-based technologies with artificial intelligence (AI) and machine learning technologies opens even wider possibilities of solution finding for precise and smart agriculture.

2. Motivation

The demand of farmers to obtain timely information about the state of the plant for a relevant response to keep the required plant conditions or to save the crop requires reliable and cost-effective solutions for plant parameter monitoring. The advantages of the UAV to perform different agricultural missions inspire us to consider the possibility of using UAVs as a multifunctional tool for plant monitoring and immediate relevant response. In this paper, we develop an algorithm based on machine learning (ML) for automatic monitoring of the condition of crops to determine the critical areas and give a quick response to the identified problems.

3. The latest research analysis

Climate change and the growth of population are the most evident challenges to modern agriculture that require searching for and studying novel solutions for the sustainable development of this branch of people activity. Several reviews study the application of UAVs for agricultural purposes. In the paper [8], the UAV application for monitoring of parameters of forage crops is reviewed. A review of different types of UAVs and their applications is made in the paper [9]. The

UAV-based remote sensing technologies in combination with machine learning are presented in the paper [10]. This paper also considers the advantages of AI algorithms for the estimation of plant needs and makes forecasts of production. The integration of UAVs, AI, and the Internet of Things (IoT) for precision agriculture is discussed in [11]. In [12] the decision-support system for agriculture works planning using UAVs as a multifunctional tool is presented and discussed. Paper [13] makes a comparison of research that is devoted to the integration of UAVs and AI. In this paper, the problems for future solutions are mentioned and are divided into the categories connected with the physical part of unmanned aircraft systems (UAS), that is, UAV. For example, the battery life is needed to finish the mission successfully. Another kind of issues for future research is connected with the cyber domain and includes tasks connected with an adaptation of learning algorithms to a random nature environment, data fusion from different sensors and processing algorithms, development of energy-efficient AI models, benchmark datasets, standardization, and others. Paper [14] provides a summary of the plant diseases and techniques of pest monitoring with deep learning DL for classification and prediction. The present limitations of the large language models were outlined in the paper as the insufficiency of the data for correct and reliable outputs. The suggestions on the combined use of the AI models were made in the paper as well. The latest research analysis proves that utilizing the new technologies for automation and productivity enhancement of modern and future agriculture is an actual task [15]. That, in turn, requires further study of the potential when integrating UAV-based technologies with artificial intelligence (AI) and machine learning technologies to develop smart agriculture.

4. Learning algorithm of plant state classification and UAV flight routing

To automatically monitor the condition of plants and crops using an unmanned aerial vehicle, an intelligent data processing pipeline was built. The process begins with the continuous collection of high-quality RGB images from a camera mounted on the UAV. The end of the process is the construction of a detailed map of the plant condition and the formation of a flight route for the targeted application of fertilizers or protective agents.

During the preparation, the footage is automatically converted to a single-color space. Then, they are scaled to a size of 50×50 pixels, and after this, each pixel block is converted into a vector with a length of 7,500 elements. These vectors form the input features for the RandomForest classifier [16], which is trained in a loop with the accuracy rate fixed on a control sample after each iteration.

The order of the automatic monitoring and flight route formation can be represented as the algorithm in Figure 1.

The algorithm can be represented as the following steps:

1. Start.
2. Formation of a learning base. For this purpose, the pictures of fields covered with plants are uploaded. Pictures include samples of plants with typical reactions (features) to diseases and samples of plants' reactions to the nutrition deficit.
3. Preliminary processing of the updated materials.
4. The next block of the algorithm represents the programming of the flight route, and then the UAV makes a flight and records the coordinates and pictures. This is the formation of the database.
5. The next stage is the processing of the images.
6. Then, the Learning of the model Random Forest based on the results of initial data processing is done.
7. The next step is the mapping of the areas of plants under different states as high-quality RGB images. The color contains information about the plant's state.
8. Storage of the data taken from the UAV in Excel.

9. The final step of the algorithm is the accuracy diagram formation.

At the preliminary stage, the randomly assigning class labels to test the pipeline's performance. The labels include 0 for healthy plants, 1 for a plant that needs fertilizer, and 2 for plants that need chemical treatment. This can be seen in detail in Figure 2. In the future, we plan to replace this conditional markup with expert or semi-automatic markup. The data is split into training (80%) and test (20%) samples once before the training cycle.

In Figure 2, the 10x10 square that represents the field is shown. Horizontal and vertical planes are the normalized field dimensions. On the right side, the color scale is shown, the scale represents the color indications of the plant state. The zero value or the green corresponds to the good conditions of the plant. In this case, no actions are required. The unit or the yellow color in Figure 2 corresponds to the conditions of plants with a lack of nutrition. In this case, fertilization is required. The number 3 or red color shows the plant that is damaged by the disease. In this case, chemical treatment is required.

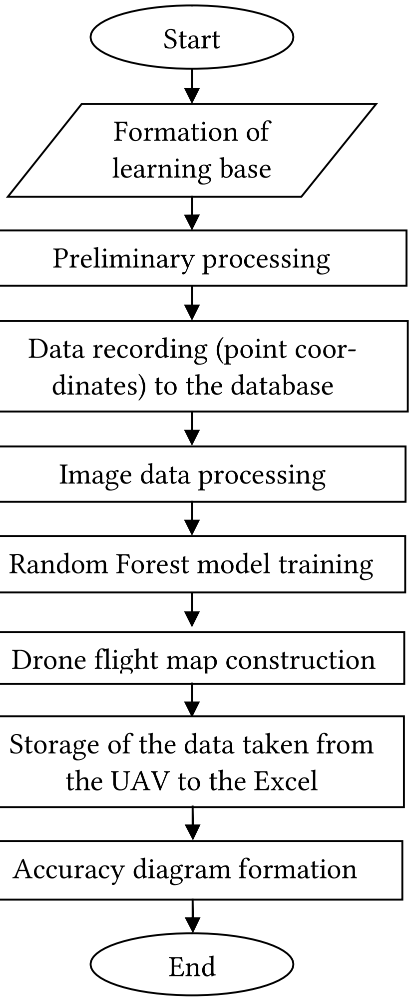

Figure 1: Algorithm of plant state monitoring, classification, and UAV flight route formation

5. Simulation and analysis

Cyclic training was performed in three key scenarios: at 10, 100, and 1000 epochs. During the first phase (epochs 1-3), the classification accuracy of the fluctuating conveyor was in the range of 40-65%. This can be seen in Figure 3, which indicates that the number of iterations was insufficient to extract stable features. By the fifth iteration of the 10-epoch scenario, the accuracy value leveled off around 40 %, while in the scenarios with 100 and 1000 epochs, a gradual increase to 60-65 % was observed.

From the analysis of Figure 3, it is possible to conclude that the number of iterations was insufficient to extract stable features.

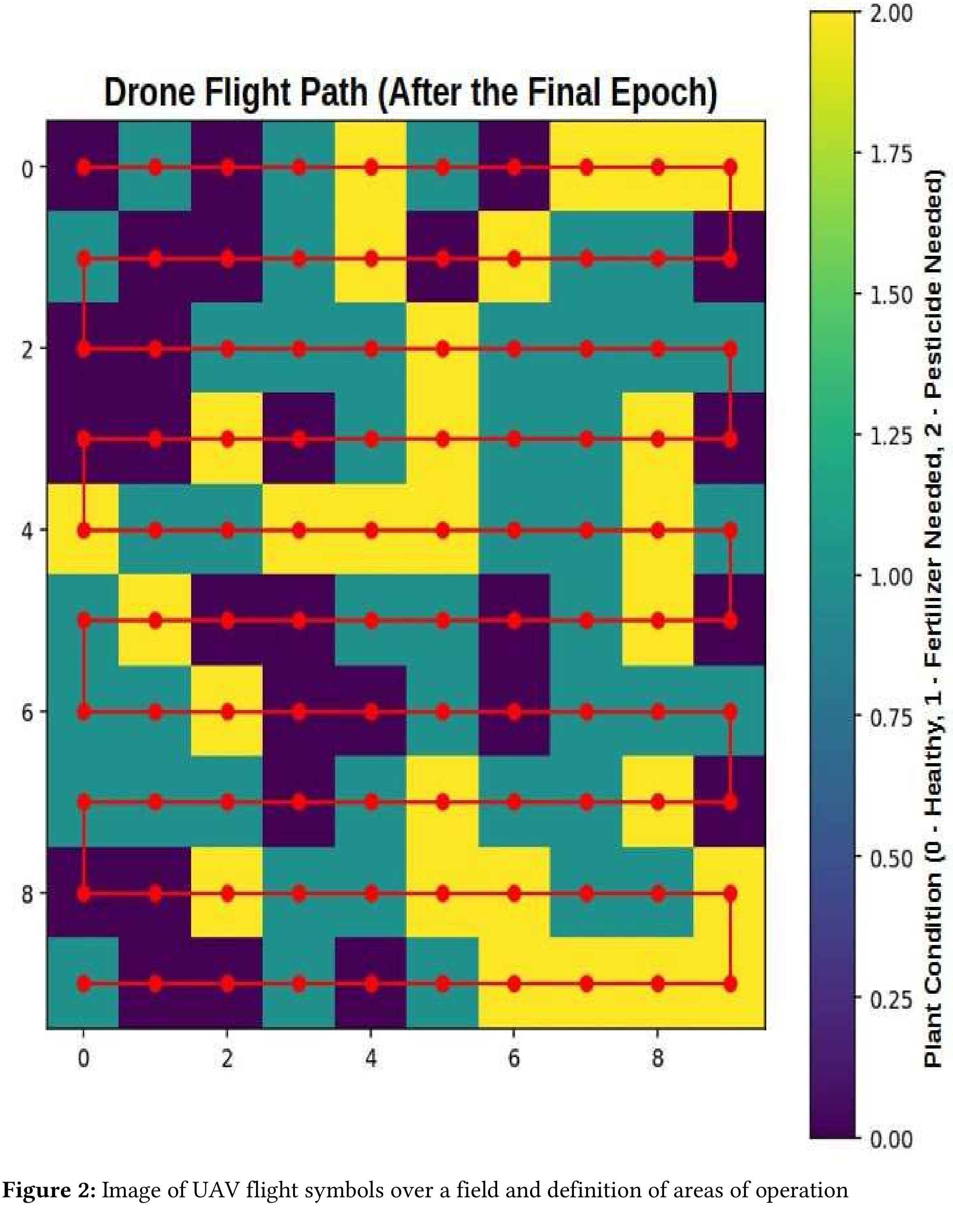

Figure 2: Image of UAV flight symbols over a field and definition of areas of operation

By the fifth iteration of the 10-epoch scenario, the accuracy value leveled off around 40%, while in the scenarios with 100 and 1000 epochs, a gradual increase to 60-65 % was observed. The Image of the learning testing scenario for 100 epochs is shown in Figure 4.

From Figure 4 it is possible to see that in the scenario with 100 epochs, the accuracy graph shows initial instability (accuracy circles fluctuate between 45 % and 60 % within the first 10-15 iterations), after which a smooth leveling off occurs: by the 30th epoch, the average accuracy value rises to ≈53 %, and in the range of 30-100 epochs, it is kept in the range of 53-57 % with a gradual decrease in the fluctuation amplitude. This indicates that the model reaches its maximum ability to generalize features with this number of training cycles and that a further increase in epochs does not yield a noticeable increase in quality.

The Image of the learning testing scenario for 1000 epochs is shown in Figure 5.

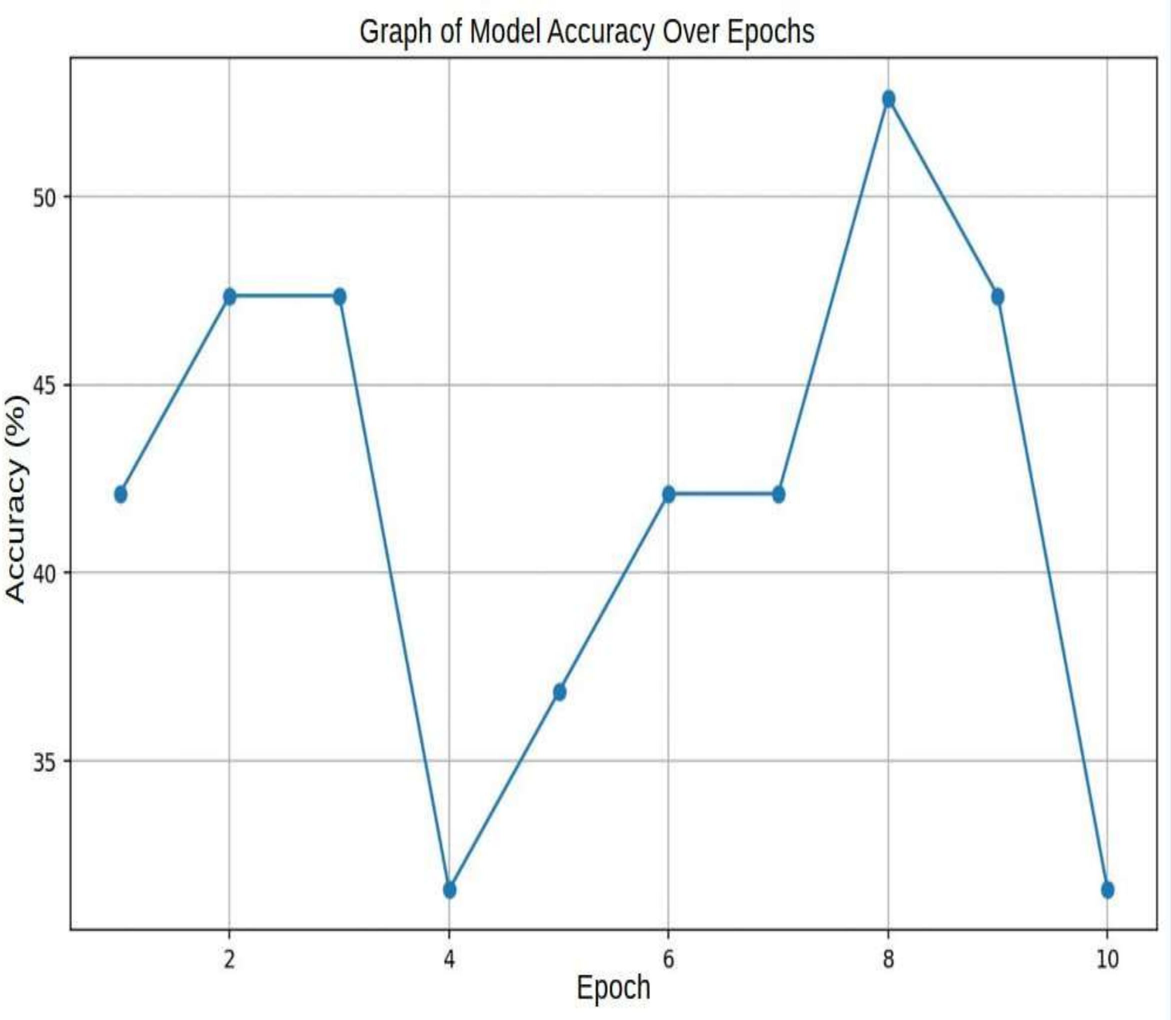

Figure 3: Image of a learning testing scenario for 10 epochs

As it is possible to see from Fig.5, in the long-term experiment with 1000 epochs, three qualitatively different intervals of accuracy development are visible. In the initial period (the first 20 epochs), the accuracy rises from ≈40% to ≈45% with high variability. Then, within about 20-200 epochs, there is a more rapid linear increase, up to ≈65 % of the average accuracy, with a gradual decrease in the amplitude of fluctuations. After the 200th epoch, the accuracy curve reaches a new plateau: the values remain around 60-62 % with fluctuations of ±1 %, which indicates that the information in the initial sample has been exhausted and the training has begun to saturate. Further training exceeds the time and computational costs without any significant performance improvement.

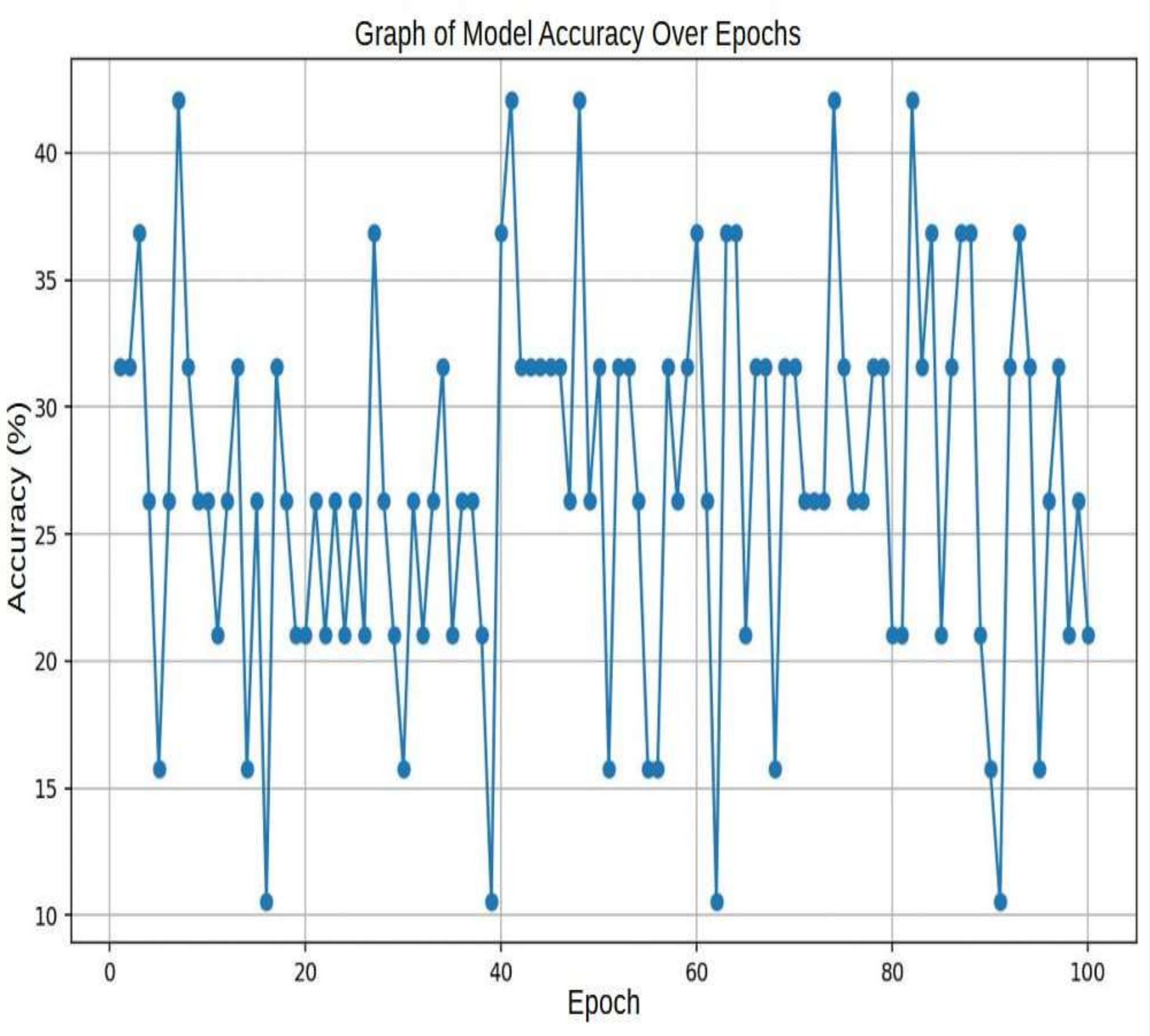

Figure 4: Image of a learning testing scenario for 100 epochs

After each epoch, a 10×10 field state matrix is automatically generated, where each element contains the predicted class of the plot. At the beginning of the training (5th epoch), the green class ('healthy') occupied about 40% of the cells, the yellow class ('need fertiliser') - 35%, and the red class ('need chemistry') - 25%. By the 50th epoch, the proportion of green cells increased to ≈60%, yellow cells decreased to ≈25%, and red cells to ≈15%. In the final maps, after 1000 epochs, the ratio stabilised at around 65% / 25% / 10%. Each of these matrices was exported to an Excel file named status_map_epoch_<k>.xlsx, which allowed for a detailed analysis of the spatial distribution of states at different points in the training.

To plan the flight, we used the snake algorithm [17], which generates a sequence of cell coordinates in such a way as to minimize empty movements. The algorithm of automatic scaling of geo data to minimize empty movements can also be found in [18,19,20]. The route was superimposed on a false-color visualization of the state matrix so that critical areas (red) were placed in the central part of the path, which ensured priority processing. The route visualization showed uniform coverage of the entire area with a minimum trajectory length and quick response to problem areas.

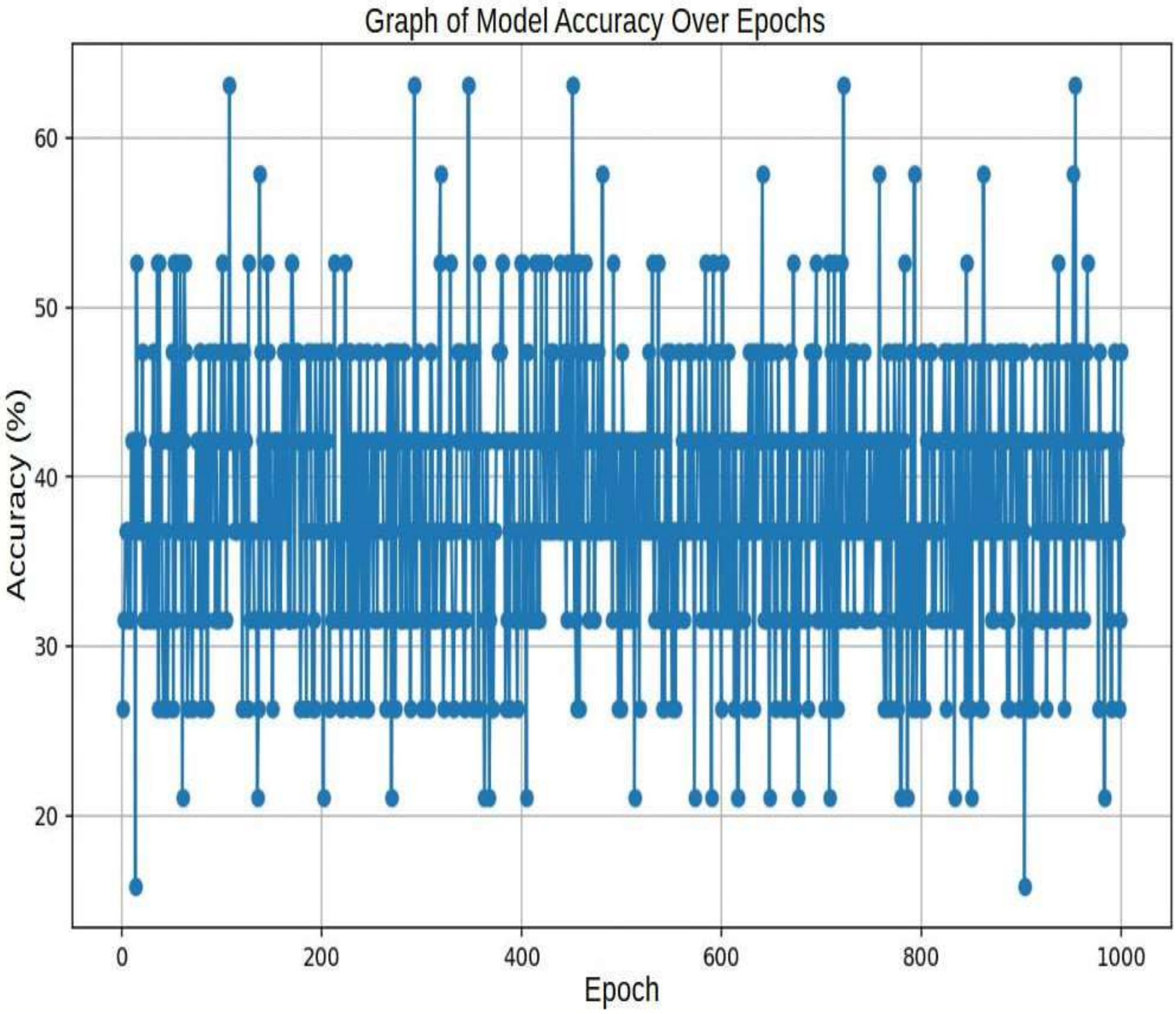

Figure 5: Image of a learning testing scenario for 1000 epochs

6. Conclusions

In this paper, we developed an ML-based algorithm for the classification of plant state and decision making about effective response. The algorithm aims to detect plants that are under the lack of nutrition or are damaged by diseases. The algorithm also provides UAV flight mapping in order to match the field points with classes of plant states.

To train the model, we used the real pictures of the field of Triticum aestivum. The visual diagnostic was made using the UAV with a camera mounted on it. The pictures of Triticum aestivum that contain characteristic features of the symptoms of damage by disease or suffering from a lack of nutrition were used as well. These symptoms are mostly revealed as a change in the coloration of certain organs and as a change in the general plant appearance. These allow to classify objects in the green class as 'healthy', in the yellow class as 'need fertilizer', and in the red class as 'need chemistry'.

Cyclic training was performed in three key scenarios: at 10, 100, and 1000 epochs. The results of the analysis demonstrated that a long-term experiment with 1000 epochs provides the highest accuracy. The peak is found within about 20-200 epochs, and the 200th epoch, where the accuracy curve reaches and remains around 60-62 % with fluctuations of ±1 %. This indicates that the information in the initial sample has been exhausted, and the training has begun to saturate. Further training exceeds the time and computational costs without any significant performance improvement.

The results of the research also demonstrate the potential of the integration of modern technologies, including UAV, artificial intelligence (AI), and machine learning, into the agricultural field of people activity, showing the advantages of considered technologies for automatic monitoring and diagnostic of the plant and quick response to treatment actions.

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Declaration on Generative AI

During the preparation of this work, the authors) used Grammarly in order to Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the publication's content.

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