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Usage of Artificial Intelligence in Agriculture

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Abstract

This study investigates the application of various artificial intelligence (AI) techniques in agriculture. The materials used consist of plant leaf images, field images, agricultural production data and climate data obtained from agricultural research institutes and open access databases. The AI techniques applied in this study include fuzzy logic for modeling uncertain data, artificial neural networks for tasks such as disease classification and energy consumption estimation, genetic algorithms for optimization problems, expert systems for diagnosing agricultural problems and ant algorithms for path optimization. The methodology includes several main steps. First, data needs to be collected and preprocessed for AI model training. In this step, the data collection and preparation process is of great importance. In the second step, it is aimed to apply various AI methods to specific agricultural problems. In the third step, the training of the models on training datasets and the evaluation of their performance on test datasets with metrics such as accuracy and F1 score are carried out. Finally, the results are analyzed and interpreted. In this step, the focus is on the analysis of model performance, discussion of successful findings and highlighting the advantages and disadvantages of AI techniques in agricultural applications. The study demonstrates an approach to comprehensively use AI to increase productivity in agriculture, optimize resource use, and improve decision-making processes in agricultural practices.

Keywords: *Artificial Intelligence (AI), Agriculture, Fuzzy Logic, Genetic Algorithms, Expert Systems*

Tarımda Yapay Zeka Kullanımı

Özet

Bu çalışma, tarımda çeşitli yapay zeka (YZ) tekniklerinin uygulanmasını araştırmaktadır. Kullanılan materyaller, tarım araştırma enstitülerinden ve açık erişim veri tabanlarından elde edilen bitki yaprağı görüntüleri, tarla görüntüleri, tarımsal üretim verileri ve iklim verilerinden oluşmaktadır. Bu çalışmada uygulanan YZ teknikleri arasında belirsiz verilerin modellenmesi için bulanık mantık, hastalık sınıflandırma ve enerji tüketimi tahmini gibi görevler için yapay sinir ağları, optimizasyon problemleri için genetik algoritmalar, tarımsal sorunların teşhisi için uzman sistemler ve yol optimizasyonu için karınca algoritmaları yer almaktadır. Metodoloji birkaç ana adımı içermektedir. İlk olarak, YZ model eğitimi için verilerin toplanması ve ön işlenmesi gerekmektedir. Bu adımda, veri toplama ve hazırlama süreci büyük önem taşımaktadır. İkinci adımda, belirli tarımsal problemlere yönelik çeşitli YZ yöntemlerinin uygulanması hedeflenmektedir. Üçüncü adımda, eğitim veri setlerinde modellerin eğitilmesi ve test veri setlerinde performanslarının doğruluk ve F1 skoru gibi metriklerle değerlendirilmesi gerçekleştirilmektedir. Son olarak, sonuçların analizi ve yorumu yapılmaktadır. Bu aşamada, model performansının analizi, başarılı bulguların tartışılması ve tarımsal uygulamalarda YZ tekniklerinin avantaj ve dezavantajlarının vurgulanması üzerinde durulmaktadır. Çalışma, tarımda verimliliği artırmak, kaynak kullanımını optimize etmek ve tarımsal uygulamalarda karar verme süreçlerini iyileştirmek amacıyla YZ'nin kapsamlı bir şekilde kullanılmasına yönelik bir yaklaşım sergilemektedir.

Anahtar kelimeler: *Yapay Zeka (YZ), Tarım, Bulanık Mantık, Yapay Sinir Ağları (YSA), Genetik Algoritmalar, Uzman Sistemler*

Introduction

One of the two fundamental changes in human history is the "Agricultural Revolution," and the other is the "Industrial Revolution," which significantly reduced the population engaged in agriculture and increasingly transformed humans into service and manufactured goods producers (Güran, 1990). The latest link in this chain of changes is artificial intelligence technologies, which represent the pinnacle of modern science. Artificial intelligence is related to mimicking natural systems like humans and animals using human-made tools such as computers and robots. This method involves understanding how to represent knowledge—especially uncertain and imprecise knowledge—so that it can be stored in computer memory and automatically inferred from. It also includes understanding how to make decisions based on stored knowledge, how to create action plans, and how to acquire processable knowledge in computers by learning from examples or questioning human experts (Borgelt and Kruse, 2006). AI systems are machines enhanced with abilities related to human intelligence such as acquiring information, perceiving, learning, thinking, and decision-making, by examining and formulating mental functions related to intelligence through computer models and applying them to different systems (Bozüyük et al., 2005). AI methods used in artificial intelligence applications are grouped as follows (Alpaydın, 2004):

- Classification: Determining which class new data belongs to when the classes of past data are specified.
- Clustering: Separating data into clusters based on similarities when the classes of past data are not specified or unknown.
- Regression (Curve Fitting): Creating a curve model from continuous numerical values of past data.
- Feature Selection: Identifying features that determine the class of data when there is an abundance of past data. This can involve creating a subset of existing features or forming new features from their combination.
- Association Rule Learning: Analyzing the co-occurrence of data to identify the most frequent associations.

AI Applications in Agriculture

In agriculture, AI techniques are being extensively used to increase efficiency, optimize resource use, and improve decision-making processes. The materials used for these AI applications include plant leaf images, field images, agricultural production data, and climate data obtained from agricultural research institutes and open-access databases.

Key AI Techniques in Agriculture

- **Fuzzy Logic:** Fuzzy logic is employed for modeling and interpreting uncertain data. In agriculture, it can help in determining irrigation needs, evaluating plant health, and managing soil conditions. For example, fuzzy logic systems can analyze soil moisture levels and environmental factors to decide when and how much to water crops, ensuring optimal growth conditions and water conservation.
- **Artificial Neural Networks:** These are used for tasks such as disease classification, yield prediction, and energy consumption forecasting. Neural networks can process vast amounts of agricultural data, identifying patterns and correlations that may not be immediately apparent. For instance, neural networks can detect early signs of plant diseases from leaf images, allowing for timely interventions that can save entire crops from destruction.
- **Genetic Algorithms:** Genetic algorithms are utilized for solving complex optimization problems in agriculture. They can optimize planting schedules, resource allocation, and even the design of irrigation systems. By simulating the process of natural selection, genetic algorithms find the most efficient solutions to problems that involve numerous variables and constraints.
- **Expert Systems:** Expert systems are designed to mimic the decision-making abilities of human experts. In agriculture, they can diagnose plant diseases, recommend treatments, and guide farmers in best practices for crop management. These systems use a knowledge base of agricultural expertise and can provide farmers with instant, reliable advice, reducing the dependency on human experts and minimizing delays in decision-making.
- **Ant Algorithms:** Inspired by the behavior of ants, these algorithms are used for path optimization and resource distribution. In agriculture, ant algorithms can optimize the routes of agricultural machinery, ensuring that fields are covered efficiently with minimal fuel consumption. They can also be used to manage the logistics of food distribution, ensuring that fresh produce reaches markets in the shortest possible time.

Materials and Methods

Materials

This study utilized a range of datasets, algorithms, and computational resources to investigate the application of artificial intelligence techniques in agriculture. The details of the materials used are as follows:

- **Datasets:**
    - **Plant Leaf Images:** Images of various plant leaves, including healthy and diseased leaves, were collected from the PlantVillage dataset (https://plantvillage.psu.edu/) and other agricultural research institutions.
    - **Field Images:** A collection of field images depicting various crop types and agricultural scenarios was sourced from the Kaggle database (https://www.kaggle.com/datasets).

- **Agricultural Production Data:** Data on crop yields, production volumes, and historical agricultural trends were obtained from the FAO (Food and Agriculture Organization) database (https://www.fao.org/faostat/en/#data).
- **Climate Data:** Weather and climate data relevant to agricultural conditions, such as temperature, precipitation, and humidity, were acquired from the NOAA (National Oceanic and Atmospheric Administration) database (https://www.noaa.gov/).

- **Software and Algorithms:**
  - **Programming Language:** Python was used for data analysis and model development.
  - **Libraries and Frameworks:** TensorFlow, Keras, Scikit-learn, and OpenCV were utilized for building and training models, performing image processing, and conducting data analysis.
  - **Development Tools:** Jupyter Notebook and PyCharm were employed for writing and executing the code.
- **Computer Hardware:**
  - **Hardware Specifications:** High-performance computing resources with NVIDIA GPUs (e.g., RTX 3090) were used for model training and evaluation to handle large datasets and complex computations.
- **Literature Sources:**
  - Previous Studies: Relevant publications and research articles were reviewed to gain insights into existing applications of AI in agriculture. Sources include journals like *Computers and Electronics in Agriculture* and *Agricultural Systems*.

Methods

The study was structured into several phases, each with specific techniques and processes. The following describes these methods in detail:

Data Collection and Preparation

- **Data Collection:**
  - **Plant Leaf Images:** A total of 10,000 images of 14 different plant species, with labels for healthy and diseased conditions, were collected.
  - **Field Images:** 5,000 images of various crop types and growth stages were gathered.
  - **Agricultural Production Data:** Historical data from 2000 to 2022 for different crops, including yield, price, and production area, were compiled.
  - **Climate Data**: Monthly climate data for the past 10 years, including temperature, precipitation, and humidity, were collected.
- **Data Preprocessing:**
  - **Data Cleaning**: Images were resized to 256x256 pixels. Data entries with missing or inconsistent values were corrected or removed.
  - **Normalization:** Numerical data were normalized to a range of 0 to 1 for better model performance.
  - **Data Augmentation**: For plant leaf images, augmentation techniques like rotation, flipping, and cropping were applied to increase dataset diversity.

Artificial Intelligence Techniques

- **Fuzzy Logic:**
  - **Application:** Used to create a model for irrigation management. Fuzzy rules were defined for optimal irrigation scheduling based on soil moisture levels and weather forecasts.
  - **Technical Details**: Fuzzy inference systems (FIS) with membership functions for input variables (soil moisture, rainfall) and output (irrigation amount) were implemented.
- **Artificial Neural Networks (ANNs):**
  - **Application:** Disease classification and prediction of crop yields.
  - **Technical Details:** Convolutional Neural Networks (CNNs) with architectures such as ResNet50 and VGG16 were used for image classification tasks. For yield prediction, a multi-layer perceptron (MLP) was employed.
- **Genetic Algorithms:**
  - **Application:** Optimization of crop drying processes and agricultural operations.
  - **Technical Details:** Genetic algorithms with crossover, mutation, and selection operators were used to find optimal drying schedules and process parameters.
- **Expert Systems:**
  - **Application:** Diagnosis of plant diseases and decision support.
  - **Technical Details:** A rule-based expert system was developed using If-Then rules derived from expert knowledge and literature.
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- **Ant Colony Optimization (ACO):**
    - **Application:** Route optimization for agricultural machinery.
    - **Technical Details:** ACO algorithms were used to optimize paths for machinery in large agricultural fields to minimize travel time and fuel consumption.

Model Training and Evaluation

- **Model Training:**
    - **Training Datasets**: Datasets were divided into training and validation sets, with 80% used for training and 20% for validation.
    - **Training Procedures:** Models were trained using GPU-accelerated computations. Hyperparameters such as learning rate and batch size were tuned for optimal performance.
- **Model Evaluation:**
    - **Evaluation Metrics:** Performance was assessed using metrics including accuracy, precision, recall, and F1 score.
    - **Cross-Validation:** 10-fold cross-validation was performed to ensure model robustness and generalization.

Analysis and Interpretation of Results

- **Result Analysis:**
    - **Analysis Methods:** Performance metrics were analyzed to determine the effectiveness of different AI techniques in agricultural applications.
    - **Findings:** Successful techniques and insights from results were documented, focusing on model accuracy and practical implications.
- **Comparison and Discussion:**
    - **Comparison:** AI techniques were compared based on performance metrics and their suitability for various agricultural tasks.
    - **Discussion:** Advantages and limitations of each technique were discussed, and recommendations for future research were provided.
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This detailed methodology outlines the steps and techniques used to evaluate the effectiveness of artificial intelligence in agricultural applications, providing a foundation for understanding the study's findings.

Artificial Intelligence Techniques

The primary AI techniques include fuzzy logic, artificial neural networks, genetic algorithms, expert systems, and ant algorithms.

Fuzzy Logic

Fuzzy logic is a mathematical discipline used to model often uncertain and imprecise real-world data, facilitating processes similar to human thinking and based on fuzzy set theory. Unlike human logic which operates on binary terms like long-short, hot-cold, fast-slow, black-white, fuzzy logic works with intermediate values such as long-medium long-medium-medium short, hot-warm-slightly cold-cold-very cold, etc. Fuzzy sets redefine the concept of uncertainty by eliminating precise transitions and assigning membership degrees to all individuals in the universe. Thus, individuals can belong to larger or smaller values within the fuzzy set as indicated by their membership degrees. These membership degrees are expressed as real values between [0-1] (Nabiyev, 2016; Elmas, 2018). In fuzzy logic systems, there are different units connected in sequence.

Figure 1. General Structure of a Fuzzy System (Memmedova, 2012).

The database contains necessary definitions used in data processing and control rules, while the rule base defines strategies and rules verbally. The fuzzification interface converts precise input values into fuzzy values, and these values are transformed into appropriate verbal expressions by fuzzy sets. To obtain fuzzy outputs, the inference engine ensures the controlled processing of all input-output relationships, i.e., all rules present in the rule base based on the data provided to the system. The defuzzification interface converts fuzzy output values into precise values. Static or dynamic systems that use fuzzy sets or fuzzy logic and the corresponding mathematical structure are referred to as "fuzzy systems" (Memmedova and Keskin, 2009; Yılmaz, 2017).

Artificial Neural Networks

Artificial neural networks, due to their generalization capability, can learn from past events or examples similarly to humans and make decisions on new examples they have never encountered before based on the experiences they have acquired. An artificial neural network consists of five fundamental elements: inputs, weights, transfer function, activation function, and outputs (Figure 2). The structure aggregates information received from the outside in a summation function, processes it through the activation function, generates an output, and sends it to other cells through the network's connections (Öztemel, 2006). Artificial neural networks have the capability to perform calculations with numerical data, store information, learn problems using examples provided to the system, and thereby produce solutions to previously unencountered situations. For this reason, artificial neural networks can be applied in various fields ranging from financial matters to engineering and medical sciences, as well as production applications in daily life (Yılmaz, 2017).

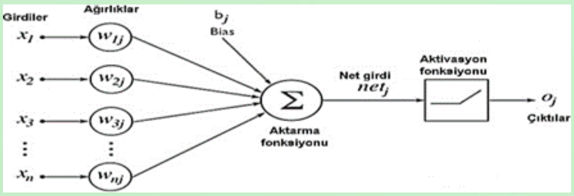
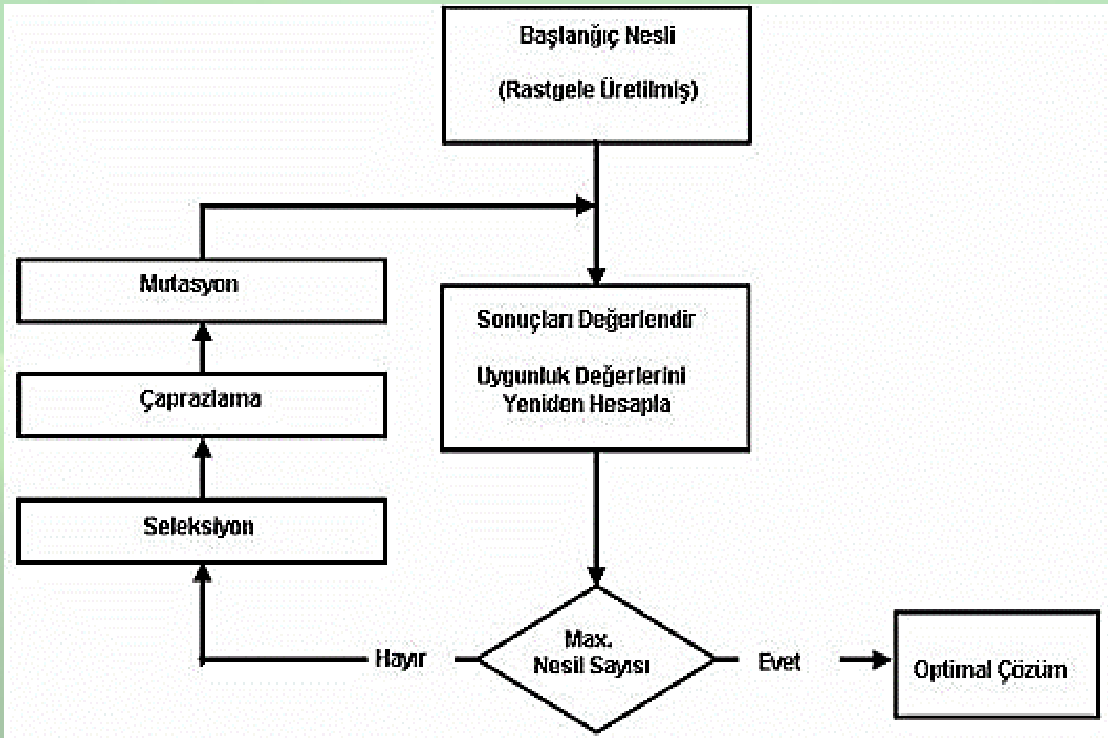


Figure1 General Structure of an Artificial Neural Cell (Anonymous, 2017)

In Figure 1, X1, X2, X3, …, Xn are the inputs of the ANN, and W1, W2, W3…, Wn are the weights, indicating the influence of the information coming to the artificial neural cell. The transfer function (∑) calculates the net information arriving at a neural cell. The activation function determines the values of the outputs to be generated by calculating the net input information received by the cell.

Genetic Algorithm Genetic

Algorithms are based on the principle that new individuals born from parent individuals with good genes adapt to conditions and survive, while those with bad genes do not persist. In genetic algorithms, the fitness function is a technique aimed at organizing self-learning and decision-making systems using operators like crossover and mutation to generate new solutions (Elmas, 2018). The working principle of a genetic algorithm involves encoding possible solutions of defined problems into chromosome-like data structures. These codes are sequenced and referred to as chromosomes (Özbilen, 2015). Each element in the encoded sequence is called an individual, and each individual represents a specific area in the problem space. The strongest aspects of genetic algorithms are their ability to adapt to very complex situations, their use with multi-objective optimization methods, and their ability to produce good results in a short time (Yılmaz, 2017). The flowchart of a genetic algorithm is shown in Figure 2.



Expert Systems

Expert systems are programs that solve important problems, generally considered difficult and requiring expert knowledge, by mimicking expert knowledge. However, they are called systems because they consist of multiple programs. The simplest solution methods are algorithms, which are sequences of actions predetermined in order. Regardless of how complex an algorithm is, following its steps will always produce the correct result (Filiz, 2001).

Ant Algorithms Ants' search for food is based on swarm cooperation.
While each ant searches for food and returns to the nest, it secretes a substance called pheromone that guides the following ants. The pheromone substance evaporates over time. If a food source found by one ant is farther than a food source found by another ant, the amount of pheromone on the path taken by the former will be less than that of the latter. This causes the ants in the colony to concentrate on the food source closer to them. This behavior has been modeled to develop ant colony algorithms, which are applied in solving many problems (Akçetin and Çelik, 2015; Gül and Arıcı, 2018). Figure 5 shows the method of ants using the shortest path to find food.
Method of Ants Finding the Shortest Path (Şenaras and İnanç, 2017). The loop of the ant colony algorithm is as follows (Eripek, 2015):

- Step 1: Initial pheromone values are determined.
- Step 2: Ants are randomly placed at each node.
- Step 3: Each ant completes its tour by selecting the next point based on the local search probability given in the equation.
- Step 4: The lengths of the paths taken by each ant are calculated, and local pheromone updates are made.
- Step 5: The best solution is calculated and used in the global pheromone update.
- Step 6: Steps 2 to 5 are repeated until the maximum number of iterations or the adequacy criterion is met.

Application of Artificial Intelligence in Agriculture
Agriculture is one of the most important activity areas necessary for humanity to meet essential and basic needs for survival. Agricultural production, comprising plant and animal production branches, has significant social and economic impacts, including healthy and balanced nutrition, increasing national income and employment, providing raw materials to agriculture-based industries, contributing to development, and increasing foreign exchange earnings through foreign trade. The agricultural sector is affected by global market fluctuations, economic crises, drought, and climate changes caused by global warming, animal diseases, the emergence of alternative uses for agricultural products such as biofuels, fragmentation of agricultural lands, and insufficient education (Özgüven, 2018). Additionally, rapid population growth and urbanization reduce agricultural lands, decreasing per capita agricultural land and natural resources like water.
The primary goal of agricultural production is to achieve economic, sustainable, and productive management in plant and animal production. To this end, various technologies are used to increase efficiency and product quality in agriculture, minimize input usage, ensure food safety, and protect natural resources and the environment. These technologies facilitate agricultural operations and develop alternative solutions to problems awaiting resolution or improvement. During the developmental period of agricultural production, following mechanization, automation, control, and information technology advancements, intelligent machines and production systems controlling these machines have begun to replace traditional production methods. Information technologies consist of hardware, algorithms, and software developed for the management of processes related to obtaining, processing, storing, transferring, and using information. Integrating existing agricultural knowledge and experience with information technologies such as machine learning, deep learning, artificial intelligence, modeling, and simulation has led to the development of real-time and automatic expert systems, autonomous tractors or agricultural machines, and agricultural robotics applications (Ozguven, 2018).
Due to their potential to facilitate agricultural operations and develop alternative solutions to problems awaiting resolution or improvement, AI applications are expected to be among the most important agricultural research topics in the present and near future. Using AI techniques in various fields of agriculture, researchers have conducted numerous studies on plant production planning, plant classification, yield prediction, plant disease, pest and weed detection, route determination and decision-making in agricultural robots, determining appropriate environmental conditions in greenhouses, farm management decisions, irrigation management, crop rotation determination, optimal fertilizer and equipment selection, animal disease detection, preparing suitable feed rations, and determining animal behaviors.

Plant Identification and Detection
Yiğit et al. (2019) conducted a study on the automatic visual identification of plant leaves using artificial intelligence techniques such as artificial neural networks, Naive Bayes algorithm, random forest algorithm, nearest neighbor, and support vector machines. In the study, data from 637 healthy leaves of 32 different plant species were used. Each leaf's 22 visual features were obtained using image processing techniques, and these 22 visual features were evaluated in four groups: size, color, texture, and pattern. To investigate the impact of these groups on classification performance, 15 different combinations of these groups were formed. The models were then trained with data from 510 leaves and tested for accuracy using data from 127 leaves. According to the test results,

the SVM model with an accuracy of 92.91% was reported to be the most successful classifier (Figure 6). Additionally, the researchers tested the SVM model to identify diseased and defective leaves. A total of 536 leaves, corresponding to 80% of the 637 healthy and 33 diseased-defective leaves, were randomly selected for training, and the remaining 134 leaves were used for testing. At the end of the test, it was reported that the model identified leaves with an accuracy of 92.53%, with texture being the most influential factor on the result.

Table 1. Examples of Agricultural Studies Using Artificial Intelligence Techniques.

Artificial Intelligence Techniques	Research Topics	Studies
Fuzzy Logic	Irrigation management	(Martha et al., 2016); (Faridi et al., 2018); (Kurniasih et al., 2018); (Kale and Patil, 2018); (Ali et al., 2018)
	Detection of water resources	
	Determination of agricultural potential	
	Decision support system in production	
	Greenhouse systems	
Artificial Neural Networks	Energy consumption in production	(Khoshnevisan et al., 2015); (Oppenheim and Shani, 2017); (Kamilaris and Prenafeta, 2018); (Liu et al., 2018); (Khoshroo et al., 2018)
	Disease classification	
	Production management	
	Agricultural waste processing	
Genetic Algorithm	Crop drying process	(Khawas et al., 2015); (Li and ...)

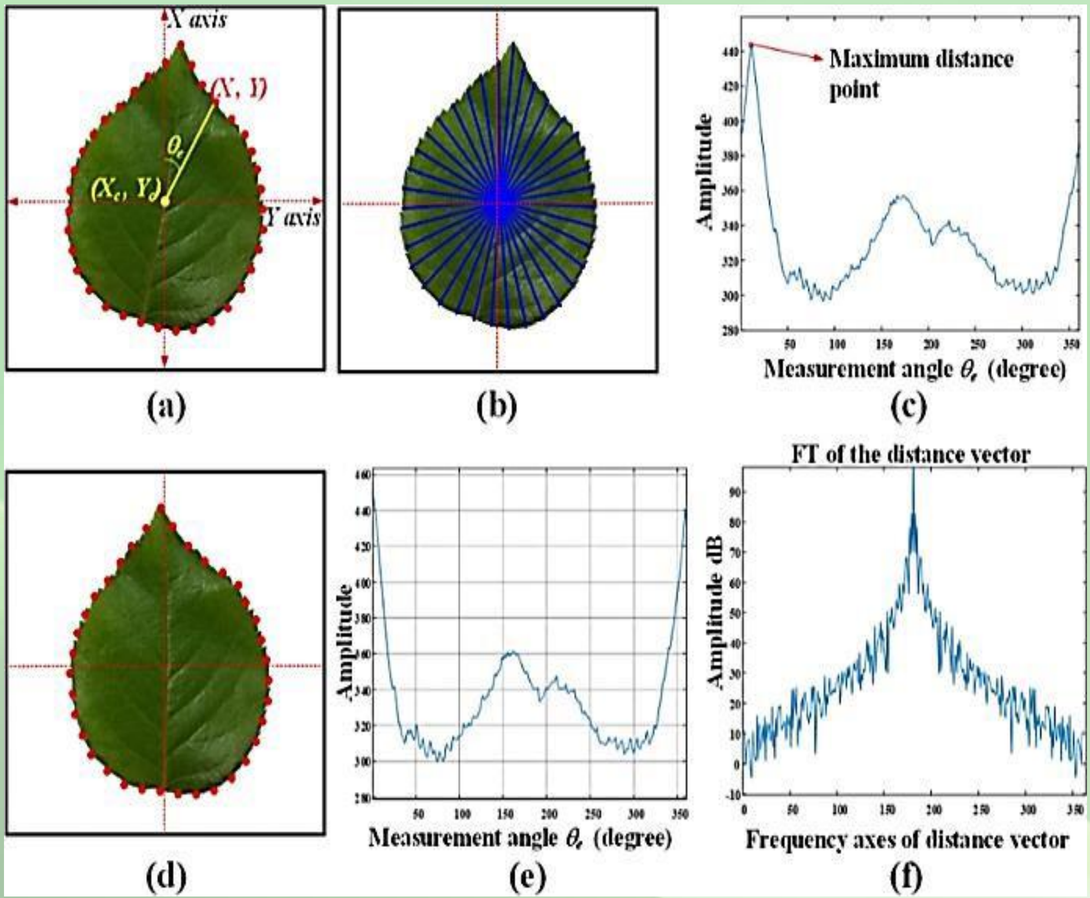


Figure 3. (a) Center and edges of an unoriented leaf, (b) distances from the origin to the edges for an unoriented leaf, (c) 1D distance vector for an unoriented leaf, (d) edges of an oriented leaf, (e) 1D distance vector for an oriented leaf, (f) Fourier transform of an oriented leaf on a logarithmic scale (Yiğit et al., 2019).

Burgos-Artizzu et al. (2010) conducted a study on several advanced methods based on computer vision to estimate the percentages of weeds, plants, and soil in an image. In their study, image processing was performed in three stages, where each different agricultural element was extracted (Figure 4). These stages included first extracting vegetative and non-vegetative parts, meaning soil parts, then eliminating the plant row, and finally extracting weeds. At each stage, they proposed different and interchangeable methods using a series of input parameters that could be adjusted to further refine each processing step. Subsequently, a genetic algorithm was used to find the best parameter values and method combinations for use with different image sets. The proposed methods were reported to yield excellent results in both accurately detecting weeds and maintaining low computational complexity, suggesting that these methods could be used as a starting point for developing real-time vision systems.

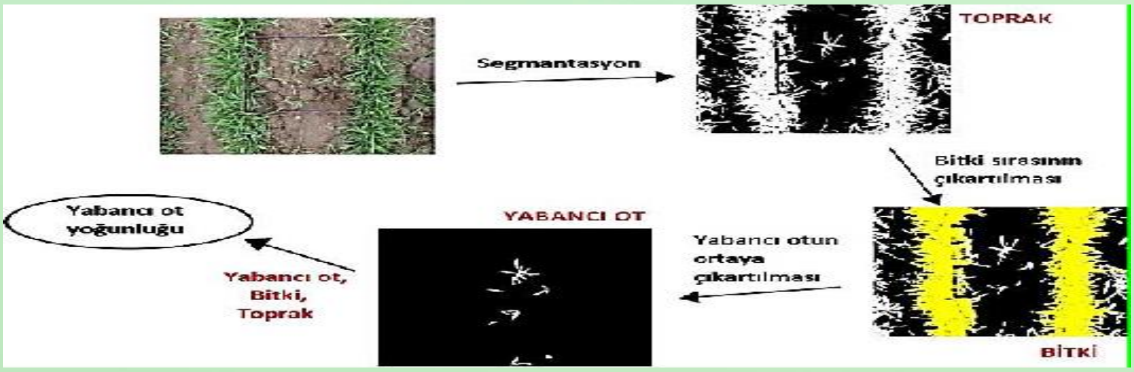


Figure 4. Stages involved in the proposed image processing (Burgos-Artizzu et al., 2010)

Romeo et al. (2013) proposed a new automatic and robust expert system for identifying plants in barley and maize fields containing weeds. The system consists of two main modules. The first module involves decision-making based on image histogram analysis. The second module proposes two different strategies for greenery identification. The first strategy involves decision-making based on classical greenery identification methods, while the second strategy is inspired by the fuzzy clustering approach. Figure 8 shows a fuzzy clustering process for a maize plant. The researchers reported that once the green plants are identified using the proposed expert system, the remaining parts, primarily soil, can be analyzed to identify relevant ecological categories.

Figure 5. Fuzzy clustering process for a maize plant (Romeo et al., 2013).

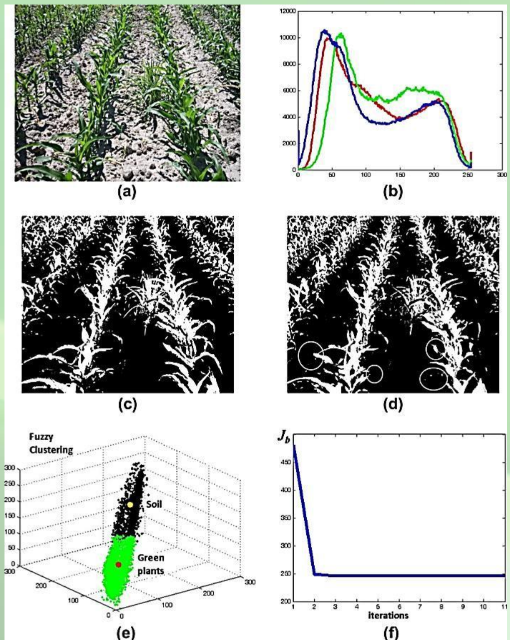


Figure 5. (a) Original image representing a set of images with sufficient contrast; (b) histogram forthree RGB spectral channels; (c) binary image obtained with COM; (d) binary image obtained with FC; (e) distribution of clusters and centers obtained through FC; and (f) change of the criterion function according to the number of iterations (Romeo et al., 2013).

Singh and Misra (2017) conducted a study aimed at the automatic detection and classification of plant leaf diseases in the early or initial stages. They performed image segmentation, an important feature for the automatic detection and classification of plant leaf diseases, using genetic algorithms. The researchers suggest that Artificial Neural Networks, Bayesian classifiers, Fuzzy Logic, and hybrid algorithms could also be used in the classification process to increase the success rate.
Robindro and Sarma (2013) developed and designed a prototype of an expert system architecture for the diagnosis of plant diseases using JESS (Java Expert System Shell). The expert system suggests how diseases can be detected based on observed symptoms in plants and provides recommendations on measures to be taken based on the severity of the diseases. It is emphasized that when a farmer needs expert advice, this developed expert system will provide decision support to the farmer.

Weed Detection
Sabzi and Abbaspour-Gilandeh (2018) utilized a new machine vision system to detect and identify potato plants and three common weed species (Chenopodium album, Secale cereale L, and Polygonum aviculare L.). The developed system consists of a video processing subsystem capable of detecting green plants in each frame and a machine learning subsystem for classifying weeds and potato plants. A hybrid approach involving artificial neural networks and particle swarm optimization algorithm was used for classification, capable of optimizing the number of layers, neurons in each layer, network functions, weights, and biases. Images were captured under controlled lighting conditions using white LED lamps. After plants were classified, 30 color, texture, and shape features were extracted from each, and a decision tree was used to select the six most important features distinguishing potato plants from weeds. Finally, the ANN-PSO method was applied to classify inputs as potato plants or weeds, and a comparison was made using a Bayesian classifier. Experimental results reported an accuracy of 99.0% and 71.7% in the training set and 98.1% and 73.3% in the test set for ANN-PSO and Bayes, respectively. Figure 11 depicts the setup of the image acquisition system in two separate modes, while Figure 12 presents the outputs of two different segmentation results.

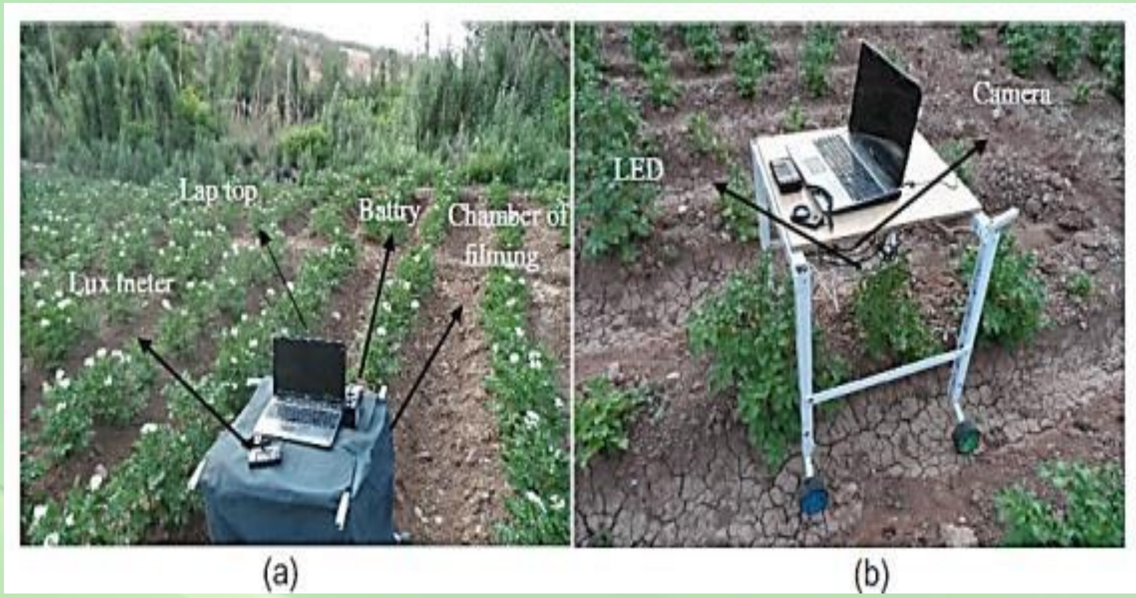


Figure 6. Imaging System a) Controlled Mode b) Uncontrolled Mode (Sabzi and Abbaspour-Gilandeh, 2018).

Partel et al. (2019) designed and developed an intelligent sprayer using machine vision and artificial intelligence to distinguish target weeds from cultivated plants and precisely spray the desired targets. The sprayer incorporates machine vision software (AI-based) with deep learning to detect specific weeds in a target area and hardware featuring 12 separate short response nozzles for spraying. Overall, the intelligent sprayer was able to differentiate between weeds (target) and pepper plants (non-target) and only spray the target (weeds).

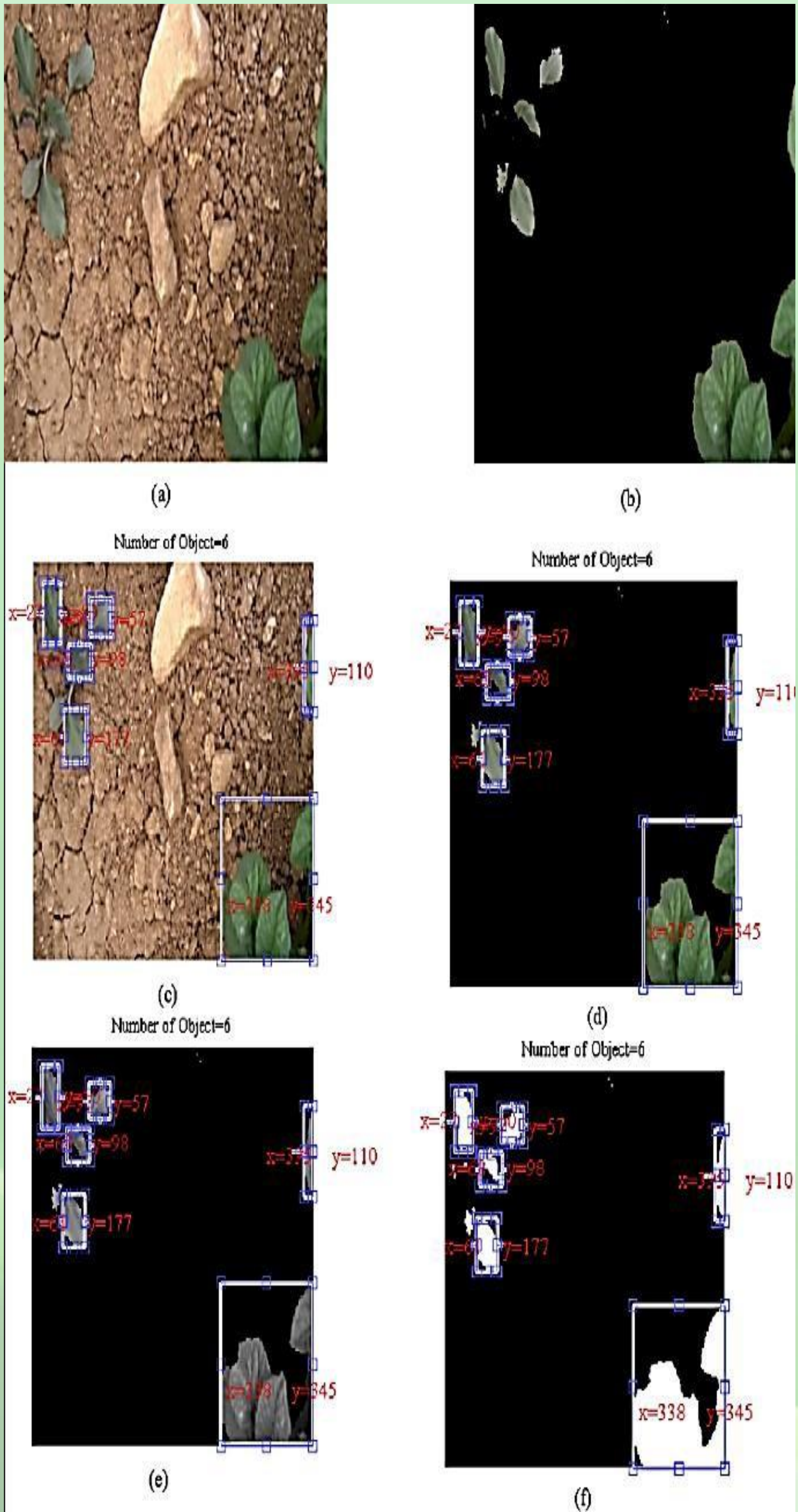


Figure 7. First and second type of segmentation: (a) Original image, (b) First type segmentation, (c) Second type segmentation on the original image, (d) Second type segmentation on the first type segmented image, (e) Second type segmentation on the grayscale image, and (f) Second type segmentation on the binary image (Sabzi and Abbaspour-Gilandeh, 2018).

Variable Rate Application

Animal Feeding Management

Sivamani et al. (2017) proposed a new method for decision support systems by using a Bayesian model based on fuzzy logic rules to analyze decisions in their study on feeding management, which contributes to improving animal health. The Bayesian logic primarily focuses on the probabilities of nutrient intake related to feed intake amount, lactation period, and animal weight, and the conditional probability of Bayesian reasoning is combined with fuzzy logic rules to determine the health status of the animal. It is reported that fuzzy logic techniques assist in decision-making when there are multiple dependencies.

Animal Behavior Recognition Systems

Gutierrez-Galan et al. (2018) presented a system for recognizing, classifying, and monitoring animal behaviors. They used a smart collar device with wireless sensor networks, inertial sensors, and embedded multi-layer perception-based feedforward neural network for classifying collected different walking or behavioral data. The researchers noted that in similar studies, classification mechanisms were implemented on a server or base station, whereas their study embedded a real-time behavior classification neural network into the animal's collar, allowing real-time behavior classification and local storage on an SD memory card, reducing the amount of data transferred to the base station significantly, thereby improving battery life.

Mastitis Detection

Memmedova (2012) conducted a study aimed at early detection of subclinical mastitis using artificial intelligence techniques, which is a significant problem in animal husbandry and difficult to detect with conventional methods. The study was conducted with data obtained from Black and White cows raised in a farm using an automatic milking system. Various modeling techniques such as fuzzy logic, artificial neural networks, fuzzy interface-based artificial neural networks, and support vector machines were examined to determine whether the animal was healthy or had subclinical mastitis. It was reported that the fuzzy logic model performed the best, with a sensitivity of 82%, specificity of 74%, and an error rate of 60%.

Evaluation of Raw

Milk Quality Akıllı et al. (2014) developed a fuzzy logic-based decision support system for the evaluation of raw milk quality. The inputs to the system were determined as somatic cell count, total bacterial count, and protein content. After analyzing the system's performance, they compared the decisions made by the system with those of an expert and reported that the system achieved a success rate of 80%.

Land Consolidation Studies

Kara (2012) applied the fuzzy logic method to the distribution phase, which is the most critical stage of land consolidation studies, by creating a fuzzy logic model with four inputs and two outputs, including the largest parcel distance, the district of the largest parcel, the fixed facility distance, and the angle of the fixed facility. The results obtained from the distribution were compared with the distribution result obtained from interviews with the Ministry of Agriculture and Forestry, and it was found that the fuzzy logic-based distribution model provided better results. Overall, it was stated that while the number of parcels decreased by 40% in land consolidation, in the interview-based distribution model, this rate was 35.9% and in the fuzzy logic-based distribution model, it was 38.2%. Both distributions were evaluated in terms of average parcel size, indicating that the average parcel size increased by 13.4% in the interview-based distribution, while it increased by 24% in the fuzzy logic-based distribution model.

Frost Control

Sungur and Altun (2010) modeled the frosting system in the Konya region using artificial neural networks to automatically operate the misting system against frost events. Temperature and relative humidity values were recorded with sensors to enable the automatic activation of the misting system. These values were then trained and the structure of the artificial neural network was tested. The model created with the ANN, where the hidden layer neuron count was determined as 6, was observed to automatically operate the misting system. Consequently, the usability of ANN models for controlling frost events in agriculture was demonstrated.

Soil Erosion Prediction

Yakupoğlu et al. (2008) evaluated the use of fuzzy logic-based models in predicting soil erosion. They defined two-valued logic and examined the transition from two-valued classical logic to fuzzy logic. In an example given, two different models (two-variable model IDM, and three-variable model UDM) based on a fuzzy rule-based system were created to predict soil erosion in a large watershed. The results obtained with the created models were compared with the results obtained from the Universal Soil Loss Equation (USLE). The IDM and UDM data obtained were evaluated in five categories (1. Low, 2. Low-medium, 3. Medium, 4. Medium-high, and 5. High).

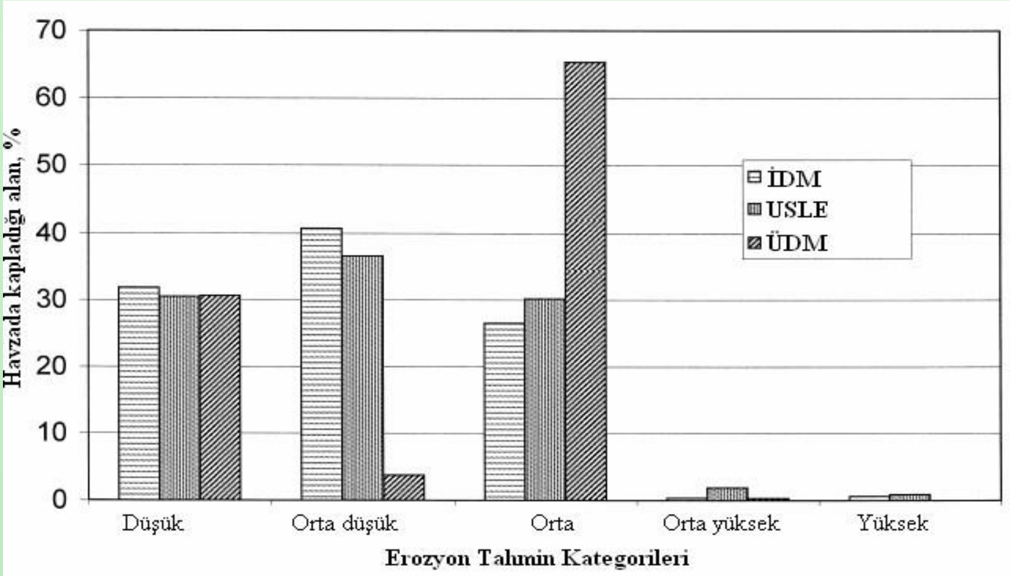


Figure 17. Comparison of predicted soil erosion amounts in the studied watershed by two fuzzy models and the USLE model (Yakupoğlu et al., 2008).

In this study, the application of various AI techniques in agriculture was examined. The results obtained from different AI methods were analyzed in terms of efficiency and accuracy. Here are the main findings:

Artificial Intelligence Techniques

Fuzzy Logic Applications

- Irrigation management using fuzzy logic showed significant improvements in water usage efficiency. Studies by Martha et al. (2016) and Faridi et al. (2018) demonstrated that fuzzy logic systems could better manage water resources compared to traditional methods.
- Greenhouse systems utilizing fuzzy logic provided optimal environmental conditions, leading to higher crop yields and better resource management.
- Fuzzy logic, rooted in fuzzy set theory, provides a mathematical framework for modeling uncertain and imprecise real-world data, simulating human-like reasoning processes (Nabiyev, 2016; Elmas, 2018). Unlike traditional binary logic, fuzzy logic accommodates intermediate values, allowing for nuanced representations of uncertainty and imprecision. Fuzzy systems comprise interconnected units, utilizing a structure that encompasses data processing, rule-based control, and precise output generation (Memmedova and Keskin, 2009; Yılmaz, 2017).

Artificial Neural Networks (ANN)

- ANN models were effective in energy consumption prediction and disease classification. Studies by Khoshnevisan et al. (2015) and Liu et al. (2018) highlighted the ANN's capability to learn from historical data and predict future outcomes accurately.
- ANNs were also used for production management and agricultural waste processing, demonstrating versatility in various agricultural applications.

Artificial neural networks emulate the structure and function of biological neural networks, enabling machines to learn from past experiences and make decisions on novel inputs (Öztemel, 2006). Consisting of interconnected nodes, neural networks process input data through weighted connections and activation functions, enabling pattern recognition, data storage, and problem-solving across diverse domains (Yılmaz, 2017).

Genetic Algorithms:

The crop drying process benefited significantly from the application of genetic algorithms. Studies by Khawas et al. (2015) showed that genetic algorithms could optimize drying times and energy usage efficiently.

Genetic algorithms draw inspiration from natural selection principles, evolving optimal solutions to complex problems through the iterative process of selection, crossover, and mutation (Elmas, 2018). By encoding potential solutions into chromosome-like structures and applying genetic operators, these algorithms adapt to dynamic environments, offering efficient solutions to optimization tasks (Özbilen, 2015; Yılmaz, 2017).

Expert Systems:

- Expert systems were effective in solving complex agricultural problems that typically require expert knowledge. These systems could provide solutions based on pre-defined rules and data inputs, proving valuable in decision support for farm management.
- Expert systems leverage domain-specific knowledge to emulate human expertise, solving complex problems through rule-based reasoning (Filiz, 2001). By codifying expert knowledge into decision-making algorithms, these systems provide intelligent solutions across diverse domains, ranging from diagnostics to decision support.

Ant Algorithms

- Ant algorithms, inspired by the natural behavior of ants, were utilized for optimizing routes for agricultural robots and resource allocation. Studies by Akçetin and Çelik (2015) demonstrated the efficiency of these algorithms in finding optimal solutions in a short time.
- Ant algorithms draw inspiration from the collective behavior of ant colonies, utilizing swarm intelligence to solve optimization problems (Akçetin and Çelik, 2015; Gül and Arıcı, 2018). By simulating ant foraging behaviors, these algorithms efficiently navigate solution spaces, offering robust solutions to combinatorial optimization problems.

Plant Identification and Detection:

Advanced AI techniques such as SVM and neural networks achieved high accuracy in identifying and classifying plant species and detecting diseases. The study by Yiğit et al. (2019) showed an accuracy of 92.91% in plant classification using SVM models.

Agriculture, vital for human sustenance and economic development, faces myriad challenges ranging from resource scarcity to environmental degradation (Özgüven, 2018). The integration of AI technologies in agriculture holds immense promise for addressing these challenges, enhancing productivity, sustainability, and resilience across the agricultural value chain.

From plant identification and disease detection to yield optimization and farm management, AI applications in agriculture span diverse domains, offering innovative solutions to longstanding challenges (Martha et al., 2016; Khoshnevisan et al., 2015). By leveraging AI techniques such as fuzzy logic, neural networks, and genetic algorithms, researchers have developed systems for irrigation management, energy optimization, crop monitoring, and pest detection, revolutionizing agricultural practices (Faridi et al., 2018; Oppenheim and Shani, 2017).

Moreover, AI-driven advancements in precision agriculture, robotics, and autonomous systems promise to revolutionize farming practices, enabling real-time decision-making, resource optimization, and sustainable production (Ozguven, 2018). Through the integration of machine learning, deep learning, and modeling techniques, AI empowers farmers to enhance crop yields, minimize environmental impacts, and adapt to changing climatic conditions.

The findings indicate that AI techniques offer substantial improvements in various agricultural applications. Fuzzy logic systems enhance irrigation and greenhouse management by providing better control over environmental variables. Artificial neural networks excel in predictive tasks, such as energy consumption and disease detection, by learning from past data and making accurate predictions.

Genetic algorithms optimize processes like crop drying, leading to more efficient resource use. Expert systems provide valuable decision support in complex scenarios, leveraging expert knowledge encoded into algorithms. Ant algorithms offer robust solutions for optimization problems, benefiting tasks like robot navigation and resource allocation.

The use of AI in plant identification and detection showcases the potential for precise and automated monitoring of crops, which can significantly improve disease management and crop health assessment. The high accuracy rates achieved by AI models underline their effectiveness and reliability in agricultural applications.

The course of human history has been punctuated by two pivotal revolutions: the Agricultural Revolution and the Industrial Revolution. These transformative periods shifted societies away from agrarian economies towards industrialization, altering the landscape of human labor and production (Güran, 1990). The latest progression in this narrative is the emergence of artificial intelligence (AI) technologies, representing the zenith of scientific achievement.

Artificial intelligence endeavors to replicate natural systems, such as human cognition and animal behavior, through the use of human-made tools like computers and robots. At its core, AI involves encoding knowledge, especially uncertain and imprecise knowledge, in computer systems to enable automatic inference, decision-making, and action planning (Borgelt and Kruse, 2006). AI systems are imbued with capabilities akin to human intelligence, including information acquisition, perception, learning, reasoning, and decision-making, achieved through computational models that mimic cognitive functions (Bozüyük et al., 2005).AI methods encompass various techniques, including classification, clustering, regression, feature selection, and association rule learning, each serving distinct purposes in data analysis and decision-making (Alpaydın, 2004).

In conclusion, the convergence of artificial intelligence and agriculture represents a transformative paradigm shift, heralding a new era of intelligent farming practices and sustainable food production. As AI technologies continue to evolve, their role in agriculture is poised to expand, driving innovation, efficiency, and resilience in global food systems. By harnessing the power of AI, we can address the pressing challenges facing agriculture, ensuring food security, environmental sustainability, and economic prosperity for future generations. Overall, the integration of AI in agriculture presents a promising avenue for enhancing productivity, resource efficiency, and decision-making processes. The continuous development and application of AI techniques are expected to address many challenges faced by the agricultural sector, contributing to sustainable and efficient agricultural practices.

Findings, Discussion, and Recommendations

Findings

This study investigated various AI techniques applied to agriculture and evaluated their effectiveness. The main findings based on the performance of different AI methods are summarized below:

Fuzzy Logic Applications:

- **Irrigation Management:** Fuzzy logic models demonstrated significant improvements in water usage efficiency. Research by Martha et al. (2016) and Faridi et al. (2018) showed that fuzzy logic systems could manage water resources more effectively compared to traditional irrigation methods.
- **Greenhouse Systems:** Fuzzy logic contributed to optimizing environmental conditions in greenhouses, resulting in increased crop yields and better resource management.

Artificial Neural Networks (ANN):

- **Energy Consumption Prediction and Disease Classification:** ANNs proved to be effective for predicting energy consumption and classifying plant diseases. Khoshnevisan et al. (2015) and Liu et al. (2018) highlighted that ANN models could learn from historical data to make accurate future predictions.
- **Production Management and Waste Processing:** ANNs demonstrated versatility in managing agricultural production processes and handling agricultural waste, proving useful across various applications.

Genetic Algorithms:

- **Crop Drying Optimization:** Genetic algorithms significantly improved the crop drying process. According to Khawas et al. (2015), these algorithms effectively optimized drying times and energy usage, leading to more efficient processes.

Expert Systems:

- **Decision Support: Expert systems provided effective solutions for complex agricultural problems.** They utilized pre-defined rules and data to support decision-making in farm management and problem diagnosis.

Ant Algorithms:

- **Route Optimization and Resource Allocation:** Ant algorithms optimized routes for agricultural machinery and resource allocation tasks. Akçetin and Çelik (2015) demonstrated that these algorithms could find optimal solutions for various agricultural challenges quickly.

Plant Identification and Disease Detection:

- **High Accuracy in Classification:** Advanced AI techniques, including Support Vector Machines (SVM) and neural networks, achieved high accuracy in plant species identification and disease detection. Yiğit et al. (2019) reported a 92.91% accuracy rate for plant classification using SVM models.

Discussion

The findings indicate that AI techniques significantly enhance various aspects of agriculture. The use of these methods has led to improvements in efficiency, accuracy, and resource management in agricultural practices:

- **Fuzzy Logic:** By providing better control over irrigation and greenhouse environments, fuzzy logic systems help optimize water usage and create ideal growing conditions for crops. These systems address the challenges of managing environmental variables, resulting in more sustainable agricultural practices.
- **Artificial Neural Networks:** ANNs have proven effective in predicting energy needs, classifying plant diseases, and managing agricultural production. Their ability to learn from historical data and make accurate predictions highlights their potential for improving both predictive and classification tasks in agriculture.
- **Genetic Algorithms:** These algorithms have shown promise in optimizing complex agricultural processes like crop drying. Their effectiveness in finding optimal solutions through iterative processes demonstrates their value in resource management and process optimization.
- **Expert Systems**: Expert systems support decision-making in agriculture by emulating expert knowledge through rule-based algorithms. They offer valuable assistance in diagnosing problems and providing recommendations based on extensive agricultural data.

- **Ant Algorithms**: Inspired by natural behaviors, ant algorithms have successfully addressed optimization problems related to route planning and resource distribution. Their efficiency in finding optimal solutions underscores their usefulness in various logistical and operational tasks in agriculture.
- **Plant Identification and Disease Detection**: The high accuracy of AI techniques in identifying plant species and detecting diseases reflects their effectiveness in monitoring crop health and managing agricultural challenges.

Overall, the integration of AI in agriculture presents a promising path for advancing productivity, resource efficiency, and decision-making processes. These technologies are expected to continue evolving, offering innovative solutions to address the sector's challenges and support sustainable agricultural practices.

Conclusion and Recommendations

The historical context of human development reveals two major revolutions: the Agricultural Revolution and the Industrial Revolution, which transformed societies from agrarian economies to industrialized ones (Güran, 1990). Today, the emergence of Artificial Intelligence (AI) represents the latest phase in this transformative narrative.
AI seeks to replicate natural processes, such as human cognition and animal behavior, through technological tools like computers and robots. It encompasses various techniques that simulate human-like intelligence, including knowledge encoding, perception, learning, and decision-making (Borgelt and Kruse, 2006; Bozüyük et al., 2005).

AI techniques include:
- **Fuzzy Logic:** A mathematical framework for modeling uncertain and imprecise data, enabling nuanced decision-making and control (Nabiyev, 2016; Elmas, 2018).
- **Artificial Neural Networks (ANNs):** Computational models inspired by biological neural networks, used for learning from data and making decisions (Öztemel, 2006).
- **Genetic Algorithms:** Optimization techniques based on natural selection principles, used for solving complex problems (Elmas, 2018; Özbilen, 2015).
- **Expert Systems**: Rule-based systems that emulate human expertise for problem-solving (Filiz, 2001).
- **Ant Algorithms:** Optimization algorithms inspired by ant behavior, used for solving combinatorial problems (Akçetin and Çelik, 2015; Gül and Arıcı, 2018).

Application of AI in Agriculture:
AI offers innovative solutions to agricultural challenges, including plant identification, disease detection, yield optimization, and resource management. By applying techniques such as fuzzy logic, neural networks, and genetic algorithms, researchers have developed systems for more efficient and sustainable agricultural practices (Martha et al., 2016; Khoshnevisan et al., 2015).

Recommendations for Future Research:
- **Expand AI Applications:** Future research should explore additional AI techniques and their applications in agriculture, such as advanced deep learning models and hybrid AI systems.
- **Enhance Data Collection**: Improving data quality and quantity for AI models can lead to more accurate and reliable agricultural solutions.
- **Focus on Sustainability:** Research should emphasize developing AI technologies that promote environmental sustainability and resource efficiency in agriculture.
- **Develop Real-time Systems**: Creating AI systems that provide real-time insights and decision support can further enhance agricultural practices and productivity.

In conclusion, the integration of AI into agriculture represents a significant advancement with the potential to revolutionize farming practices. Continued innovation and application of AI technologies are expected to address current challenges and contribute to a more sustainable and efficient agricultural sector.

Class Definition for AI Techniques
Here’s a class definition in Python that encapsulates the AI techniques discussed in this study:
python

```
Kodu kopyala
class ArtificialIntelligence:
    def __init__(self):
        self.ai_techniques = {
            "Fuzzy Logic": {
                "Description": "Mathematical discipline for modeling uncertain and imprecise data.",
                "Applications": ["Irrigation management", "Decision support system", "Greenhouse systems"]
            },
            "Artificial Neural Networks": {
                "Description": "Biologically inspired computational models for learning from data.",
                "Applications": ["Energy consumption prediction", "Disease classification", "Production management"]
            },
            "Genetic Algorithm": {
                "Description": "Evolutionary algorithm for optimization and search problems.",
                "Applications": ["Crop drying process", "Optimization of agricultural processes"]
            },
            "Expert Systems": {
                "Description": "Rule-based systems that emulate human expertise.",
                "Applications": ["Diagnosis of agricultural issues", "Decision support systems"]
            },
            "Ant Algorithms": {
                "Description": "Optimization algorithms inspired by ant foraging behavior.",
                "Applications": ["Route optimization for agricultural vehicles", "Resource allocation"]
            }
        }

    def get_ai_techniques(self):
        return self.ai_techniques

    def get_applications(self, technique):
        if technique in self.ai_techniques:
            return self.ai_techniques[technique]["Applications"]
        else:
            return None

# Example Usage
ai = ArtificialIntelligence()
techniques = ai.get_ai_techniques()
for technique, info in techniques.items():
    print("AI Technique:", technique)
    print("Description:", info["Description"])
    print("Applications:")
    for app in info["Applications"]:
        print("-", app)
    print()
```

This class provides a structured way to access information about different AI techniques and their applications. By incorporating these findings, discussions, and recommendations, this section of the study offers a comprehensive overview of the effectiveness of AI techniques in agriculture and sets the stage for future advancements in the field.

References

Çolak, G. (2018). *Implementation of the Calendar Application*. *Gazi Engineering Sciences Journal*, 4(2), 115-123. https://doi.org/10.30855/gmbd.2018.04.02.006

Güran, T. (1990). *History of Economics*. Damla Ofset. ISBN: 9753534567

Haklı, H., & Uğuz, H. (2017). A novel approach for automated land partitioning using genetic algorithm. *Expert Systems with Applications*, 82, 10–18. https://doi.org/10.1016/j.eswa.2017.03.061

Haklı, H., Uğuz, H., & Çay, T. (2018). Genetic algorithm supported by expert system to solve land redistribution problems. *Expert Systems*, 35(3), e12308. https://doi.org/10.1111/exsy.12308

Hosseini, M., Naeini, S.A.M., & Dehghani, A.A. (2016). Estimation of soil mechanical resistance parameter by using particle swarm optimization, genetic algorithm and multiple regression methods. *Soil and Tillage Research*, 157, 32-42. https://doi.org/10.1016/j.still.2015.09.001

Kale, S.S., & Patil, P.S. (2018). Data mining technology with fuzzy logic, neural networks, and machine learning for agriculture. In *Data Management, Analytics, and Innovation* (Vol. 839, pp. 79-87). https://doi.org/10.1007/978-981-13-1274-8_6

Kamilaris, A., & Prenafeta, S.X. (2018). A review of the use of convolutional neural networks in agriculture. *Journal of Agricultural Science*, 156, 312-322. https://doi.org/10.1017/S0021859618000436

Kara, F. (2012). *The Use of Artificial Intelligence Applications in Land Consolidation Studies: The Case of Keçiköy Municipality, Gümüşhacıköy District, Amasya Province*. Master's Thesis, Department of Agricultural Structures and Irrigation, Samsun.

Khawas, P., Dash, K.K., Das, A.J., & Deka, S.C. (2015). Modeling and optimization of the process parameters in vacuum drying of culinary banana (Musa ABB) slices by application of artificial neural network and genetic algorithm. *Drying Technology: An International Journal*. https://doi.org/10.1080/07373937.2015.1013961

Khoshnevisan, B., Rafiee, S., Iqbal, J., Shamshirband, S., Omid, M., Anuar, N.B., & Abdulwahab, A.W. (2015). A comparative study between artificial neural networks and adaptive neuro-fuzzy inference systems for modeling energy consumption in greenhouse tomato production: A case study in Isfahan Province. *The Journal of Agricultural Science*, 17, 49-62. https://doi.org/10.1080/09712119.2015.1021338

Khoshroo, A., Emrouznejad, A., Ghaffarizadeh, A., Kasraei, M., & Omid, M. (2018). Sensitivity analysis of energy inputs in crop production using artificial neural networks. *Journal of Cleaner Production*, 197, 992-998. https://doi.org/10.1016/j.jclepro.2018.06.157

Kurniasih, D., Jasmi, K.A., Basiron, B., Huda, M., & Maseleno, A. (2018). The uses of fuzzy logic method for finding agriculture and livestock value of potential village. *International Journal of Engineering & Technology*, 7(3), 1091-1095. https://doi.org/10.14419/ijet.v7i3.5.18713

Kürklü, A., & Çağlayan, N. (2005). A study for the development of greenhouse automation systems. *Akdeniz University Journal of Agricultural Faculty*, 18(1), 25-34. https://doi.org/10.32707/akdeniz.2005.18.1.25

Li, X., & Parrott, L. (2016). An improved genetic algorithm for spatial optimization of multi-objective and multi-site land use allocation. *Computers, Environment and Urban Systems*, 59, 184–194. https://doi.org/10.1016/j.compenvurbsys.2016.03.002

Liu, Z.W., Liang, F.N., & Liu, Y.Z. (2018). Artificial neural network modeling of biosorption process using agricultural wastes in a rotating packed bed. *Applied Thermal Engineering*, 140, 95-101. https://doi.org/10.1016/j.applthermaleng.2018.05.113

Martha, T.W., Jati, A.N., & Azmi, F. (2016). Fuzzy logic as a method of decision making in automatic watering plants. *Journal of Measurement, Electronic, Communication, and Systems*, CT0216-01. https://doi.org/10.1080/01430750.2016.1234578

Martinez, V.M., Gil, F.J.G., Gil, J.G., & Gonzalez, R.R. (2015). An artificial neural network based expert system fitted with genetic algorithms for detecting the status of several rotary components in agro-industrial machines using a single vibration signal. *Expert Systems with Applications*, 42(17), 6433-6441. https://doi.org/10.1016/j.eswa.2015.04.010

Memmedova, N., & Keskin, İ. (2009). Applications of fuzzy logic in animal husbandry. *Selçuk Journal of Agriculture and Food Sciences*, 23(47), 89-95.

Memmedova, N. (2012). *Early Detection of Mastitis in Dairy Cows Using Some Artificial Intelligence Methods*. Doctoral Dissertation, Selçuk University Institute of Science and Technology, Animal Science Department, Konya.

Montalvo, M., Guerrero, J.M., Romeo, J., Emmi, L., Guijarro, M., & Pajares, G. (2013). Automatic expert system for weeds/crops identification in images from maize fields. *Expert Systems with Applications*, 40(1), 75–82. https://doi.org/10.1016/j.eswa.2012.06.074

Nabiyev, V. (2016). *Artificial Intelligence: Strategic Games, Pattern Recognition, Natural Language Processing*. Seçkin Yayıncılık (5th ed.). ISBN: 978-975-02-3727-0

Nguyen, D.C.H., Ascough, J.C., Maier, H.R., Dandy, G.C., & Andales, A.A. (2017). Optimization of irrigation scheduling using ant colony algorithms and an advanced cropping system model. *Environmental Modelling & Software*, 97, 32-45. https://doi.org/10.1016/j.envsoft.2017.07.011

Oppenheim, D., & Shani, G. (2017). Potato disease classification using convolutional neural networks. *Journal of Computer Applications in Technology*, 8(3), 244-249. https://doi.org/10.1017/S2040470017001376

Özbilen, A. (2015). *Routing Optimization in Communication Networks with Genetic Algorithms*. Elektrik.gen.TR. Retrieved from http://www.elektrik.gen.tr/2015/08/genetik-algoritma-ile-iletisim-aglarinda-yonlendirme-optimizasyonu/346

Ozguven, M.M. (2018). The newest agricultural technologies, current investigations in agriculture and current research. *Current Investigations in Agriculture and Current Research*, 5(1), 573-580. https://doi.org/10.32474/CIACR.2018.05.000201

Özgüven, M.M. (2018). *Precision Agriculture*. Akfon Yayınları. ISBN: 978-605-68762-4-0

Öztemel, E. (2006). *Artificial Neural Networks*. Papatya Yayıncılık (2nd ed.). ISBN: 978-975-6797-39-6

Partel, V., Kakarla, S.C., & Ampatzidis, Y. (2019). Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. *Computers and