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Artificial neural networks and adaptive neuro-fuzzy inference system networks' application in crop production

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ABSTRACT

In the dynamic realm of agriculture, where intricate interactions between environmental factors and human interventions dictate crop outcomes, the pursuit of innovation has long been a driving force. Within this context, artificial intelligence (AI) has emerged as a catalyst for precision and efficiency, offering transformative potential in crop production. Among the diverse branches of AI, artificial neural networks (ANNs) and their adaptive counterparts, particularly the fuzzy logic/fuzzy inference system (FIS) and adaptive neuro-fuzzy inference system (ANFIS) emerged as robust tools poised to revolutionize agriculture. Inspired by the complexities of the human brain, ANNs represent a paradigm shift in understanding and optimizing crop production systems, offering remarkable abilities to discern patterns, extract insights, and adapt to changing environmental conditions. This chapter embarks on an illuminating journey into the realm of artificial and adaptive neural networks, delving deep into their applications and implications in crop production. Through a meticulous exploration of their architecture, functionality, and real-world applications, the transformative potential of ANNs in optimizing yields, mitigating risks, and fostering resilience in agricultural ecosystems is revealed. From predictive modeling and precision agriculture to resource allocation optimization and decision-making enhancement, ANNs and ANFISs emerge as catalysts of innovation, propelling the agricultural sector toward a future defined by sustainability and productivity.

Keywords: *Fuzzy logic, fuzzy inference system, ANN, ANFIS, energy optimization*

1. Introduction

In the vast expanse of agricultural landscapes, where the delicate dance between environmental factors and human intervention dictates the fate of harvests, the quest for innovation has perennially been a driving force[18,20,34]. At the nexus of this pursuit lies the burgeoning realm of artificial intelligence (AI), heralding a new era of precision and efficiency in crop production[5,12,13,14,15,16,22]. Among the myriad branches of AI, artificial neural networks (ANNs) and their adaptive counterparts particularly the fuzzy logic/ fuzzy inference system (FIS) and adaptive neuro-fuzzy inference system (ANFIS) stand as formidable tools[18,19,23,24,31,36], poised to revolutionize the agricultural landscape[7,25,38,39]. Harnessing the underlying principles of neural networks inspired by the intricacies of the human brain[8,45], ANNs offer a paradigm shift in the understanding and optimization of crop production systems[24,38]. As digital architects of intelligence, ANNs possess the remarkable ability to discern patterns, extract insights, and adapt to dynamic environmental conditions with unparalleled dexterity[20,39]. This intrinsic adaptability renders them indispensable assets in the quest for sustainable agricultural practices[23,31,45]. In this chapter, we embark on an illuminating journey into the realm of artificial and adaptive neural networks[41], delving deep into their applications and implications in the realm of crop production[24]. Through a meticulous exploration of their architecture, functionality, and real-world applications[26], we uncover the transformative potential of ANNs in optimizing yields[45], mitigating risks, and fostering resilience in agricultural ecosystems[18,24]. From predictive modeling and precision agriculture to the optimization of resource allocation and the enhancement of decision-making processes[9,23], ANNs emerge as catalysts of innovation, driving the agricultural sector towards a future defined by sustainability and productivity[8,24]. With each layer of neural connectivity, we peel back the layers of complexity shrouding crop production, unraveling a tapestry of insights and possibilities that promise to redefine the boundaries of agricultural excellence[18]. As we navigate the fertile terrain of artificial and adaptive neural networks in crop production[8,18], we stand at the precipice of a technological renaissance, where the fusion of human ingenuity and machine intelligence heralds a new dawn for agriculture.

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2. Artificial Neural Networks (ANNs): Modeling intelligence inspired by the human brain

ANNs represent a class of computational models inspired by the structure and function of biological neural networks found in the human brain[24]. ANNs have gained prominence across various fields[24], including machine learning, pattern recognition, and data analysis[11], owing to their ability to learn complex patterns, make predictions, and perform tasks that were previously thought to require human intelligence[8,18]. In this detailed exploration, we delve into the architecture, functioning, learning algorithms, and diverse applications of ANNs, elucidating their pivotal role in modern computing and decision-making processes[41,20].

2.1. Architecture of ANNs
At its core, an artificial neural network comprises interconnected nodes, or neurons, organized into layers[41]. The simplest form of an ANN consists of three layers: an input layer, one or more hidden layers, and an output layer[24]. Neurons within each layer are connected to neurons in adjacent layers through weighted connections, which transmit signals and modulate the strength of information flow throughout the network[18]. The architecture of an ANN can vary widely depending on the specific task it is designed to perform[24], with more complex architectures featuring additional hidden layers and specialized types of neurons (Figure 1)[18].

2.2. Functioning of ANNs
The functioning of an artificial neural network is characterized by a process known as forward propagation[41], wherein input data is passed through the network layer by layer, undergoing transformation and computation at each neuron (Figure 2). Each neuron in the hidden layers applies an activation function to the weighted sum of its inputs, introducing non-linearity and enabling the network to learn complex relationships within the data[18]. The output layer produces predictions or classifications based on the final activation patterns generated by the network[18]. During training, the network adjusts the weights of its connections using a process called back-propagation, wherein errors between predicted and actual outputs are propagated backward through the network, allowing it to learn and refine its internal representations iteratively[45].

2.3. Learning Algorithms in ANNs
Several learning algorithms are used to train artificial neural networks, with the most common being gradient descent-based optimization techniques such as stochastic gradient descent (SGD), back-propagation, and variants thereof[41]. These algorithms iteratively adjust the weights of network connections in response to observed errors, seeking to minimize a predefined loss function that quantifies the disparity between predicted and actual outputs. Additionally, regularization techniques such as dropout, weight decay, and early stopping are employed to prevent over-fitting and improve the generalization ability of neural network models, ensuring robust performance on unseen data.

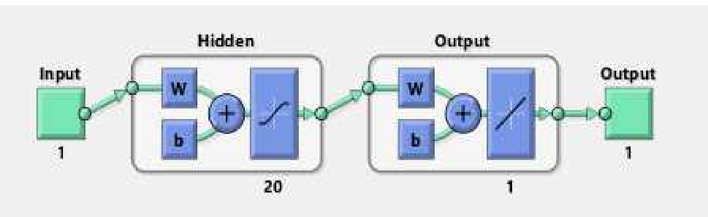

Figure 2. *An illustration of the artificial neural networks (ANNs) model developed for the prediction of crop yields.*

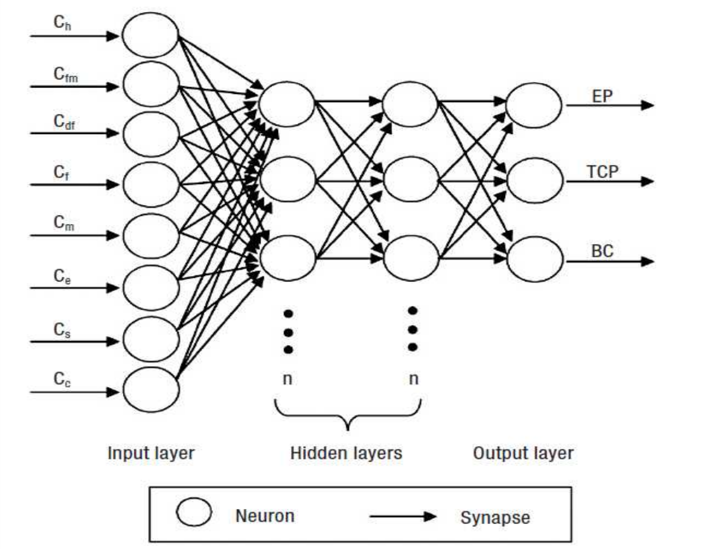

Figure 1. *Diagrammatic representation of multi-layer feed-forward neural networks used for modeling economic productivity (EP), total production cost (TCP), and benefit-cost ratio (BC) used for potato production in Iran (Adapted from [45]).*

3. Adaptive Neuro-Fuzzy Inference Systems (ANFIS): Blending fuzzy logic and neural networks for intelligent decision-making
ANFIS represents a hybrid computational framework that combines the strengths of fuzzy logic and neural networks to model complex systems characterized by uncertainty, imprecision, and nonlinearity[3,7,25,35]. ANFIS leverages the linguistic modeling capabilities of fuzzy logic to capture qualitative relationships between input and output variables[27,28] while harnessing the learning and optimization capabilities of neural networks to adaptively adjust model parameters and improve accuracy[25,40]. In this detailed exploration, we delve into the architecture, functioning, learning mechanisms, and diverse applications of ANFIS, elucidating its significance in solving real-world problems across various domains[19,25,36,37].

3.1. Architecture of ANFISs
The architecture of an ANFIS comprises five main components (Figure 2).

(I) ***Fuzzy sets and linguistic variables*** **(Layer-1)**
ANFIS uses linguistic variables and fuzzy sets to represent input and output variables in a human-interpretable manner[36,42]. Each linguistic variable is associated with fuzzy sets that describe its membership functions, capturing the qualitative semantics of the variable[27,28,40].

(ii) ***Fuzzy inference system (FIS)*** **(Layer-2)**
The FIS defines the rules that govern the mapping between input and output variables[40]. These rules are expressed in the form of fuzzy '*if-then rules*', which encode expert knowledge and domain-specific heuristics (Figure 3)[3,36,37].

(iii) ***Membership function layer*** **(Layer-3)**
The membership function (MFs) layer computes the degree of membership of input variables to each fuzzy set, using *Gaussian* or triangular MFs[40]. This layer serves to fuzzify the crisp input data and transform it into linguistic terms[3,27,28].

(iv) ***Rule layer*** **(Layer-4)**
The rule layer computes the firing strengths of each fuzzy rule by combining the degrees of membership of input variables to

the antecedents of the rules[40]. This layer aggregates the fuzzy information from the MF's layer and generates rule activations[36,37].

(v) **Normalization layer and defuzzification (Layer-5)**
The normalization layer computes the normalized firing strengths of each rule, which are then used to compute the weighted average of the consequent parameters. Finally, the defuzzification process aggregates the weighted consequent parameters to produce the crisp output[36,37].

The functioning of an ANFIS involves two main phases, viz. training and inference phase (Figure 4). During the training phase, ANFIS adaptively adjusts its parameters using a combination of gradient descent and least squares optimization techniques[2,7,40]. This process involves forward propagation of input data through the FIS[36,37], followed by back-propagation of errors to update the parameters of the MFs and consequent parameters[10].In the inference phase, ANFIS applies the learned model to make predictions or decisions based on new input data[40]. The input data is fuzzified using the membership function layer, and the fuzzy inference rules are evaluated to determine the output of the system[35]. The final output is obtained through defuzzification, which converts the fuzzy output into a crisp value[27,28]. An ANFIS model developed to predict the grain yield of irrigated wheat in Abyek town of Ghazvin province, Iran has been illustrated in Figure 5 [25].

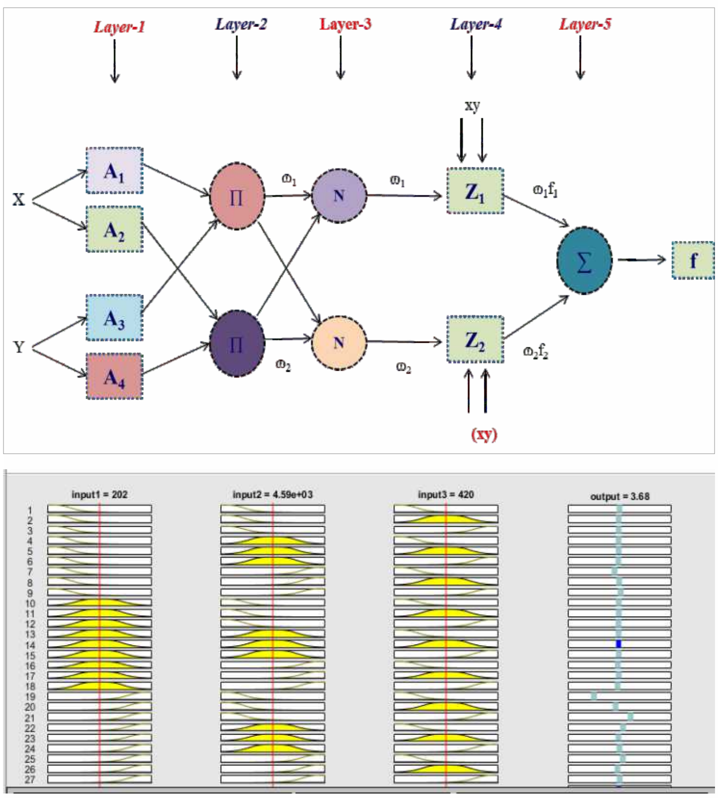

Figure 3. Diagrammatic representation of the structure of multi-layer adaptive neuro-fuzzy inference system (ANFIS) system.

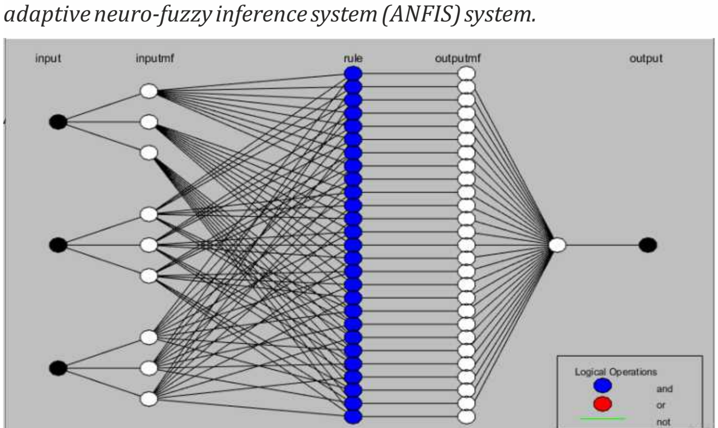

Figure 4. Network configuration of multi-layer adaptive neuro-fuzzy inference system (ANFIS) system.

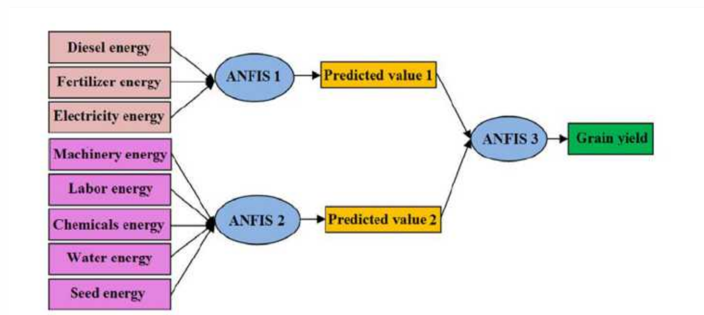

Figure 5. ANFIS model topredict the grain yield of irrigated wheat in Abyek town of Ghazvin province, Iran. (Adopted from[25]Naderloo et al., 2012)

3.2. Applications of ANNs and ANFISs in crop yield prediction

In the realm of precision agriculture, the accurate prediction of crop yields plays a pivotal role in informing management decisions, optimizing resource allocation[32,43,46], and mitigating risks associated with fluctuating environmental conditions[8,25]. Artificial intelligence techniques, particularly ANN and ANFIS have emerged as powerful tools for crop yield prediction[24,45], offering unprecedented accuracy and flexibility in modeling complex relationships between agronomic factors and crop productivity[18,19,24,25].

ANNs, inspired by the biological neural networks of the human brain, are computational models comprised of interconnected nodes, or neurons, organized into layers. Through a process of iterative learning, ANNs can discern patterns and relationships within datasets, enabling them to make predictions based on input variables. In the context of crop yield prediction[45], ANNs have demonstrated remarkable efficacy in capturing non-linear relationships between environmental variables and crop performance[8,18].ANNs excel in handling large and diverse datasets[45], making them well-suited for incorporating a wide range of agronomic parameters such as soil characteristics[47], weather patterns, crop management practices, and genetic factors. By training on historical yield data and corresponding environmental variables, ANNs can learn complex patterns and trends, thereby enabling accurate predictions of future crop yields[24]. Nonetheless, ANNs exhibit a high degree of adaptability, allowing them to adjust their internal parameters in response to changes in environmental conditions or input data[24].

This inherent flexibility enhances the robustness of ANN-based crop yield models, ensuring their applicability across diverse geographic regions and cropping systems[18]. One of the key advantages of ANNs is their ability to handle uncertainties and noisy data, which are inherent in agricultural datasets[8,19]. Through techniques such as dropout regularization and ensemble learning, ANNs can mitigate over-fitting and improve the generalization ability of crop yield prediction models, thereby enhancing their reliability in real-world applications[8].

ANFIS represents a hybrid AI approach that combines the strengths of neural networks and fuzzy logic to model complex systems characterized by uncertainty and imprecision[18,19]. ANFIS integrates fuzzy logic principles for linguistic modeling with neural network techniques for parameter optimization, resulting in a powerful framework for data-driven inference[25].In the context of crop yield prediction, ANFIS offers several advantages over traditional statistical models and purely data-driven approaches[25]. By incorporating expert knowledge in the form of linguistic rules, ANFIS can capture the qualitative relationships between input variables and crop yields, complementing the quantitative insights provided by neural networks.ANFIS models are particularly adept at handling uncertainty and imprecision in agricultural data sets, which arise from factors such as variability in soil properties[6,47], weather fluctuations, and subjective interpretations of agronomic practices[25]. By employing fuzzy logic-based inference mechanisms, ANFIS can effectively reason with uncertain and incomplete information, thereby improving the robustness and interpretability of crop yield prediction models. Additionally, ANFIS models are inherently transparent and interpretable, allowing agronomists and decision-makers to gain insights into the underlying factors driving crop productivity[19]. This interpretability enhances the trust and acceptance of ANFIS-based predictions in agricultural decision-making processes and facilitating the adoption of data-driven management strategies.

3.3. Applications and case studies

The application of ANN and ANFIS techniques in crop yield prediction spans a diverse array of crops and agroecological regions worldwide[24]. From staple cereals such as maize, wheat, and rice to cash crops like soybeans, cotton, and sugarcane, ANN and ANFIS models have been deployed to forecast yields with high accuracy and reliability[8,18,24]. Researchers have developed ANN-based models to predict maize yields based on soil properties[6,47], weather variables, and agronomic practices, achieving prediction accuracies exceeding traditional regression-based approaches. Similarly, ANFIS models have been employed to forecast rice yields in response to varying irrigation schedules and fertilizer applications, providing valuable insights for optimizing water and nutrient management strategies[18]. By integrating historical yield data with biophysical factors such as temperature regimes, soil moisture levels, and crop phenology, ANN and ANFIS models have enabled growers to anticipate fruit yields and plan harvest operations more effectively[8,19,47].

4. Applications of ANNs and ANFISs in energy optimization in crop production

Efficient energy utilization is a cornerstone of sustainable agriculture, crucial for maximizing productivity while minimizing environmental impact. Contextually, ANNs and ANFISs have emerged as indispensable tools, offering innovative solutions for energy optimization in crop production systems[19,24]. Through their ability to model complex relationships and adapt to dynamic environmental conditions, ANN and ANFIS techniques hold immense potential for enhancing energy efficiency[25], reducing resource inputs, and promoting sustainable practices across agricultural landscapes[8,24]. In the context of energy optimization in crop production, ANNs offer several key advantages:

1. Predictive modeling: ANNs excel in predicting energy consumption patterns and optimizing energy usage in various agricultural operations, such as irrigation, machinery operation, and greenhouse management[8,18]. By analyzing historical energy consumption data alongside environmental variables such as weather conditions, crop growth stages, and soil moisture levels, soil thermal resistivity ANNs can forecast energy demands and recommend optimal strategies for energy allocation[6,24,47].

2. Resource allocation: ANNs facilitate efficient resource allocation by optimizing the timing and intensity of energy inputs throughout the crop production cycle[8,24]. By integrating real-time sensor data and monitoring systems, ANNs can dynamically adjust energy usage based on crop growth dynamics, pest pressures, and other agronomic factors, thereby minimizing waste and maximizing resource utilization[18].

3. Decision support systems: ANNs serve as powerful decision support tools for farmers and agricultural stakeholders, providing actionable insights for optimizing energy-intensive processes [24]such as irrigation scheduling, nutrient management, and crop protection[18]. By leveraging ANNs to analyze complex datasets and identify energy-saving opportunities, farmers can make informed decisions that enhance productivity while reducing their environmental footprint[19,24].

Conversely, ANFIS offers several unique capabilities:

1. Linguistic modeling: ANFIS integrates expert knowledge and domain-specific rules into its modeling framework, allowing it to capture qualitative relationships between input variables and energy consumption patterns[19]. By incorporating fuzzy logic-based inference mechanisms, ANFIS can reason with uncertain and imprecise data, enhancing the robustness and interpretability of energy optimization models.

2. Rule-based control systems: ANFIS enables the development of rule-based control systems for optimizing energy usage in crop production operations. By encoding domain-specific rules and heuristics into the inference process, ANFIS can generate adaptive control strategies that respond dynamically to changing environmental conditions and crop requirements, thereby maximizing energy efficiency and minimizing waste.

3. Model interpretability: ANFIS models are inherently transparent and interpretable, allowing agricultural stakeholders to gain insights into the underlying factors driving energy consumption and optimization[18]. By visualizing the fuzzy inference process and linguistic rules, ANFIS facilitates collaboration and decision-making among farmers, agronomists, and energy experts, fostering a holistic approach to energy management in agriculture.

4.1. Applications and case studies

The application of ANN and ANFIS techniques in energy optimization in crop production spans a wide range of agricultural systems and practices[24]. From precision irrigation and mechanized farming to renewable energy integration and greenhouse automation, ANN and ANFIS models have been deployed to optimize energy usage and reduce environmental footprint in diverse cropping systems worldwide. For example, researchers have developed ANN-based models to predict energy requirements for irrigation scheduling, taking into account factors such as crop water demand, soil moisture levels, and irrigation system efficiency[47]. By optimizing irrigation scheduling based on ANN predictions, farmers can minimize energy usage while maintaining optimal soil moisture levels, thereby conserving water resources and reducing pumping costs. Similarly, ANFIS techniques have been applied to optimize energy usage in greenhouse environments, where maintaining optimal temperature and humidity levels is critical for crop growth and productivity. By integrating sensor data and climate control systems with ANFIS-based control algorithms, greenhouse operators can dynamically adjust heating, cooling, and ventilation systems to minimize energy consumption while ensuring optimal growing conditions[30]. Moreover, the integration of renewable energy sources such as solar and wind power with ANN and ANFIS models has further enhanced energy optimization in agriculture[19,24]. By leveraging predictive modeling and optimization techniques, farmers can maximize the utilization of renewable energy resources while minimizing reliance on fossil fuels, thereby reducing greenhouse gas emissions and mitigating climate change impacts[2].

5. Applications of ANNs and ANFIS in mitigating greenhouse gas emissions in crop production

The imperative to mitigate greenhouse gas (GHG) emissions in agriculture has become increasingly urgent as the global community grapples with the challenges of climate change[29]. An ANN and ANFIS emerged as powerful tools for identifying, quantifying, and mitigating GHG emissions associated with crop production systems[24]. By leveraging their capabilities in modeling complex relationships and optimizing management strategies, ANN and ANFIS techniques offer innovative solutions for reducing agricultural emissions and promoting climate-resilient farming practices[19]. In the context of mitigating GHG emissions in crop production, ANNs offer several key advantages:

1. Emission modeling: ANNs excel in modeling and predicting GHG emissions from agricultural activities, such as enteric fermentation, manure management, fertilizer application, and soil organic matter decomposition. By analyzing historical emission data alongside environmental variables like soil properties, climate conditions, and management practices, these ANNs can quantify emissions and identify key drivers of GHG emission contributors.

2. Optimization of management practices: ANNs facilitate the optimization of management practices to reduce GHG emissions while maintaining crop productivity. By simulating different scenarios and evaluating the impact of management interventions on emissions, ANNs can identify the strategies to cut down emissions intensity per unit of yield by optimizing fertilizer application rates, implementing conservation tillage practices, and integrating cover crops into cropping systems.

3. Decision support systems: ANNs serve as decision support tools for farmers, policymakers, and agricultural stakeholders by providing actionable insights for designing climate-smart farming systems. With the Integration of emission modeling with agronomic data and economic considerations, ANNs enable informed decision-making that balances environmental sustainability with economic viability, thereby fostering the adoption of emission-reducing practices at scale.

Similarly, in the context of GHG emissions mitigation in crop production, ANFIS offers several unique capabilities:

1. Linguistic modeling: ANFIS integrates expert knowledge and domain-specific rules into its modeling framework, allowing it to capture qualitative relationships between input variables and GHG emissions[19]. By incorporating fuzzy logic-based inference mechanisms, ANFIS can reason with uncertain and imprecise data, enhancing the robustness and interpretability of emission mitigation models.

2. Rule-based control systems: ANFIS enables the development of rule-based control systems for optimizing management practices to reduce GHG emissions. By encoding domain-specific rules and heuristics into the inference process, ANFIS can generate adaptive management strategies that respond dynamically to changing environmental conditions and emission sources, thereby maximizing emission reductions while minimizing trade-offs with other agronomic objectives.

3. Model interpretability: ANFIS models are inherently transparent and interpretable, allowing stakeholders to gain insights into the underlying factors driving GHG emissions and mitigation strategies. By visualizing the fuzzy inference process and linguistic rules, ANFIS facilitates collaboration and decision-making among farmers, agronomists, and policymakers, fostering a participatory approach to emission reduction in agriculture.

5.1. Applications and case studies

The application of ANN and ANFIS techniques in GHG emissions mitigation in crop production spans a wide range of agricultural systems and practices. From precision nutrient management and conservation agriculture to livestock waste management and renewable energy integration, ANN and ANFIS models have been deployed not only to optimize management strategies and also to reduce the emissions intensity in diverse cropping systems worldwide. For example, researchers have developed ANN-based models to predict GHG emissions from livestock operations, taking into account factors such as feed composition, animal physiology, and manure management practices. By simulating different feeding regimes and manure-handling techniques, ANN models can identify strategies for minimizing methane and nitrous oxide emissions from livestock production while maintaining animal productivity and welfare. Similarly, ANFIS techniques have been applied to optimize fertilizer application rates and timing in crop production systems, aiming to reduce nitrous oxide emissions from soil nitrogen sources. By integrating soil moisture data, crop nutrient requirements, and weather forecasts with ANFIS-based decision support systems, farmers can optimize nutrient management practices to minimize emissions with enhancement in nutrient use efficiency and crop yields. Moreover, the integration of renewable energy sources such as solar and bioenergy with ANN and ANFIS models has further enhanced emission mitigation efforts in agriculture. By leveraging predictive modeling and optimization techniques, farmers can maximize the utilization of renewable energy resources while minimizing reliance on fossil fuels, thereby reducing emissions from energy-intensive operations such as irrigation, machinery operation, and heating[30].

6. Applications of ANNs and ANFISs in mitigating environmental impacts in crop production

In the face of escalating environmental challenges, the agricultural sector is under increasing pressure to adopt sustainable practices that minimize negative impacts on ecosystems and natural resources[4]. Recently, ANNs and ANFISs have been emerged as powerful tools for mitigating environmental impacts in crop production, offering innovative solutions for optimizing resource use[44], reducing pollution, and promoting ecosystem resilience[17]. Through their ability to model complex relationships and optimize management strategies, ANN and ANFIS techniques provide valuable insights and decision support for designing environmentally sustainable farming systems[21]. Through iterative learning processes, ANNs can discern patterns and relationships within datasets, enabling them to make predictions and optimizations based on input variables. In the context of mitigating environmental impacts in crop production, ANNs offer several key advantages:

1. Environmental Modeling: ANNs excel in modeling and predicting environmental impacts associated with agricultural activities, such as soil erosion[1], water pollution, and habitat loss[21]. By analyzing historical environmental data alongside agronomic variables such as land use, crop rotation, and tillage practices, ANNs can quantify impacts and identify key drivers contributing to environmental degradation[44].

2. Optimization of management practices: ANNs facilitate the optimization of management practices to reduce environmental impacts while maintaining crop productivity. By simulating different scenarios and evaluating the impact of management interventions on environmental outcomes, ANNs can identify strategies for minimizing pollution, conserving natural resources, and enhancing biodiversity within agricultural landscapes[44].

3. Decision support systems: ANNs serve as decision support tools for farmers, policymakers, and environmental stakeholders, providing actionable insights for designing sustainable farming systems. By integrating environmental modeling with socio-economic considerations, ANNs enable informed decision-making that balances environmental conservation with economic viability, thereby fostering the adoption of environmentally sustainable practices at scale.
Similarly, ANFIS offers several unique capabilities *viz.*

1. Linguistic modeling: ANFIS integrates expert knowledge and domain-specific rules into its modeling framework, allowing it to capture qualitative relationships between input variables and environmental impacts. By incorporating fuzzy logic-based inference mechanisms, ANFIS can reason with uncertain and imprecise data, enhancing the robustness and interpretability of environmental impact models.

2. Rule-based control systems: ANFIS enables the development of rule-based control systems for optimizing management practices to reduce environmental impacts. By encoding domain-specific rules and heuristics into the inference process, ANFIS can generate adaptive management strategies that respond dynamically to changing environmental conditions and landscape characteristics, thereby maximizing environmental benefits while minimizing trade-offs with other agronomic objectives.

3. Model interpretability: ANFIS models are inherently transparent and interpretable, allowing stakeholders to gain insights into the underlying factors driving environmental impacts and mitigation strategies. By visualizing the fuzzy inference process and linguistic rules, ANFIS facilitates collaboration and decision-making among farmers, agronomists, and environmental experts, fostering a participatory approach to environmental management in agriculture.

6.1. Applications and case studies

The application of ANN and ANFIS techniques in mitigating environmental impacts in crop production spans a wide range of agricultural systems and practices[21]. From soil conservation and water management to pesticide reduction and habitat restoration, ANN and ANFIS models have been deployed to optimize management strategies and promote environmental sustainability in diverse cropping systems worldwide. For example, researchers have developed ANN-based models to predict soil erosion rates and identify high-risk areas prone to erosion within agricultural landscapes[1]. By integrating soil properties, topographic data, and land use information with ANN predictions, farmers can implement targeted erosion control measures such as contour plowing, cover cropping, and terracing, thereby reducing soil loss and preserving soil fertility[1].
Similarly, ANFIS techniques have been applied to optimize pesticide application rates and minimize off-site pollution in agricultural watersheds. By analyzing pesticide transport pathways, hydrological dynamics, and ecological risk factors, ANFIS models can recommend spatially targeted application strategies that minimize environmental exposure while maximizing pest control efficacy, thereby reducing ecological risks and protecting water quality. Moreover, the integration of ecosystem services such as pollination, pest control, and nutrient cycling into ANN and ANFIS models has further enhanced environmental sustainability in agriculture. By quantifying the benefits of ecosystem services and incorporating them into decision-making processes, farmers can design landscape-level management strategies that promote biodiversity, resilience, and ecosystem health, thereby fostering a synergistic relationship between agriculture and the environment.
In the initial configuration, Figure 6 portrays that input parameters were partitioned into three distinct groups, with each group serving as input variables for individual ANFIS networks [19]. The outputs generated by ANFIS networks 1–3 were subsequently fed into ANFIS 4 to forecast grain yield. The alternative arrangement consisted of seven ANFIS networks. In this setup, energy inputs were initially clustered into four groups, with each group being inputted into a separate ANFIS network (Figure 6). ANFIS 5 was constructed from the outputs of ANFIS-1 and 2, while ANFIS-3 and 4 outputs were amalgamated as inputs for ANFIS-6. Ultimately, the outputs of ANFIS-5 and 6 were integrated to form ANFIS-7, responsible for predicting wheat yield.

In the third topology, input parameters were divided into five segments, each individually serving as inputs for separate ANFIS networks. Consequently, five ANFIS networks were established in the initial stage. ANFIS-6 was then created from the forecasted values of ANFIS 1 and 2, with ANFIS 3–5 outputs subsequently employed in ANFIS-7. In the final stage, ANFIS 8 was tasked with modeling yield using the predicted values from ANFIS-6 and 7 [19] (Figure 6).

Sefeedpari *et al.* [33] introduced an innovative approach utilizing ANFIS for predicting egg yield, subsequently comparing its performance with that of an ANN model. In their study, an ANFIS model was constructed wherein inputs were segregated into two distinct groups: the first group comprised feed supply, fuel, and machinery, while the second cluster included pullet, electricity, and labor energies. Subsequently, the outputs from these networks were fed into the ANFIS-3 network to obtain predicted values of fruit yield (Figure 7). The evaluation of the ANFIS 3 network yielded a coefficient of determination (R^2) of 0.92, root mean square error (RMSE) of 448.1, and mean absolute percentage error (MAPE) of 0.014.

These results were indicated the efficacy of the ANFIS model in predicting egg yield on poultry farms accurately. Furthermore, comparative analysis with ANN models revealed statistical parameters of R^2 = 0.81, RMSE = 751.96, and MAPE = 0.019, highlighting the superior performance of ANFIS in this context. As a recommendation for future research endeavors, the authors suggest exploring ANFIS models with multi-layered structures to ascertain the optimal number of layers, potentially enhancing predictive accuracy and model robustness.

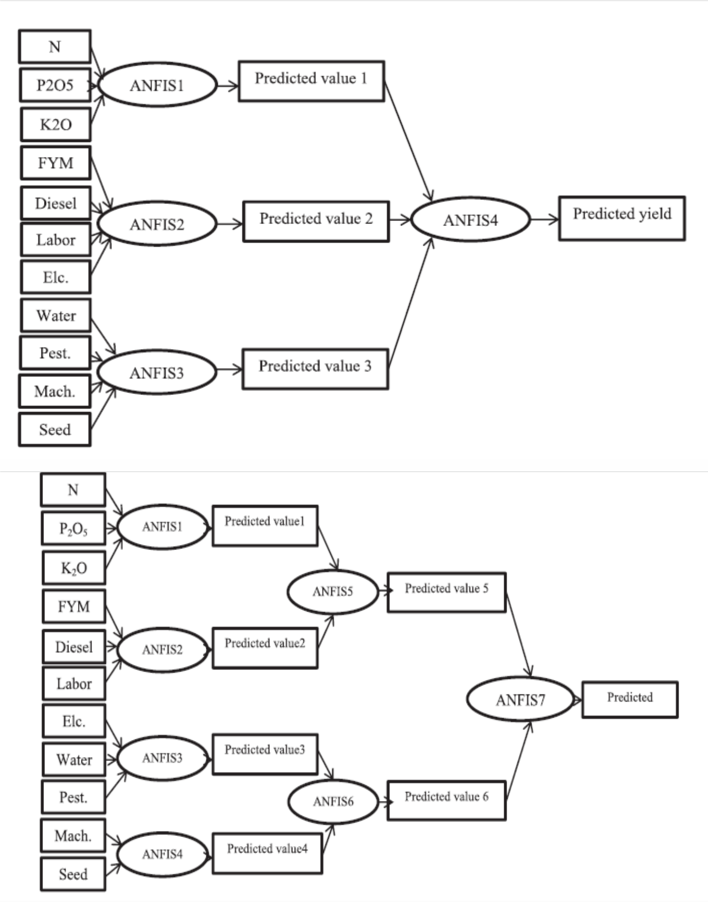

Figure 6. *ANFIS-1 (top pane) and ANFIS-1 (ubottom pane) developed for predicting wheat grain yield based on energy inputs. (Adopted from [19])*

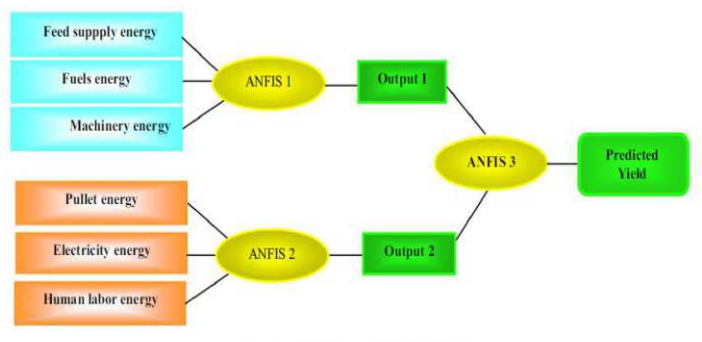

Figure 7. *ANFIS model was developed for prophesying egg production based on energy consumption. (Adopted from [33])*

7. Conclusions

In conclusion, ANN and ANFIS stand as formidable pillars in revolutionizing various facets of crop production, offering robust solutions to intricate challenges faced by the agricultural sector. These advanced modeling techniques provide unparalleled accuracy, flexibility, and interpretability in predicting crop yield, optimizing energy usage, mitigating GHG emissions, and minimizing environmental impacts. The integration of ANN and ANFIS models with cutting-edge technologies such as remote sensing, IoT, precision agriculture, and renewable energy holds immense promise for enhancing the efficiency, sustainability, and resilience of crop production systems worldwide. By harnessing the power of artificial intelligence to model complex relationships, adapt to dynamic environmental conditions, and optimize resource management, farmers and agricultural stakeholders can navigate the complexities of modern agriculture with precision and foresight. As the global community intensifies efforts to address pressing challenges of climate change, food security, and environmental degradation. The adoption of ANN and ANFIS techniques are pivotal towards achieving the goal of practicing sustainable agricultural methods . By fostering collaboration, innovation, and knowledge exchange, the integration of ANN and ANFIS models into agricultural decision-making processes can catalyze transformative change, ushering in a new era of resilience, productivity, and sustainability in crop production. In summary, the transformative potential of ANN and ANFIS extends far beyond their individual applications, shaping the future of agriculture and paving the way for a more resilient, sustainable, and equitable food system.

Future scope of study: In agriculture, where complex environmental circumstances and human interventions affect crop yields, innovation has traditionally driven progress. In this aspect, artificial intelligence (AI) has disrupted agricultural production by improving precision and efficiency. Artificial neural networks (ANNs) and its adaptive counterparts, such as the fuzzy logic/fuzzy inference system (FIS) and the adaptive neuro-fuzzy inference system (ANFIS), are strong AI tools that might alter agriculture. But these tools are new especially to the farmers. Therefore role of extension scientists especially Krishi Vigyan Kendras which are working in between the farmers could played a pivotal role by empowering the farmers with trainings related to these AI tools. By using these tools farmers could easily made their agriculture sustainable after reducing different inputs footprints viz. water, fertilizers, insecticides etc. Agriculture production system knowledge and optimisation are transformed by artificial neural networks (ANNs). They are inspired by the human brain and have exceptional ability to identify patterns, extract insights, and adapt to changing environmental conditions. There is a huge scope for carrying out the research experiments in this direction under different agro-climatic conditions and texturally divergent soils for its wider application.

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