Circular
Agricultural Systems

MINI REVIEW

Open Access

https://doi.org/10.48130/cas-0025-0001
Circular Agricultural Systems **2025**, 5: e003

Applications of Artificial Intelligence in sorghum and millet farming

Innocent Kutyauripo[1*], Munyaradzi Rushambwa[2] and Rajkumar Palaniappan[3]

[1] *Department of Agricultural Education, Ministry of Lands, Agriculture, Fisheries, Water and Rural Development, No. 1, 5th Street Extension, Harare, Zimbabwe*
[2] *Electronic Engineering Department, School of Engineering and Technology, Harare Institute of Technology, 15015 Ganges Road, Harare, Zimbabwe*
[3] *Department of Mechatronics Engineering, College of Engineering, University of Technology, Bahrain*
* Corresponding author, E-mail: ikutyauripo@gmail.com

Abstract

Many traditional African small grains have been neglected and underutilized. The small grains are neglected even though they are nutritionally rich and are resilient to the changing climate. Modern technology in the name of artificial intelligence is being applied in various crop production. The application of artificial intelligence in farming has proven to yield positive results. This paper seeks to establish whether artificial intelligence is being applied to small grains like in any other crop. A systematic review following a PRISMA reporting structure was utilized in this study. The review targets the application of artificial intelligence in sorghum and millet production. The results indicated that Artificial Intelligence can be utilized in sorghum and millet land evaluation, cropping, disease, and weed management. However, results were lacking in sorghum and millet harvesting. Based on the review it is conclusive that artificial intelligence can be applied in sorghum and millet production just like in any other grain crop. It is recommended that more research on the application of artificial intelligence be conducted to develop Artificial Intelligence programs in all aspects of sorghum and millet farming.

Citation: Kutyauripo I, Rushambwa M, Palaniappan R. 2025. Applications of Artificial Intelligence in sorghum and millet farming. *Circular Agricultural Systems* 5: e003 https://doi.org/10.48130/cas-0025-0001

Introduction

Millet is ranked third in terms of importance in Africa though it is under utilised both in terms of livestock feed and human food. Production costs are low for millets as they have a short growing period thereby resulting in lower requirements in terms of pesticides and fertilizers. Pearl millet has higher energy than wheat and rice[1]. Sorghum is a crop that is climate resilient and is mostly utilised during drought periods for both human food and animal feed. Sorghum is among the top five cultivated cereals worldwide[2,3]. This crop is mostly utilised in periods of drought when the usual crops have been greatly affected. A population of 300 million relies on sorghum in Sub Sahara Africa[3]. Sorghum has been reported to possess some medicinal properties including anti-diabetic, cancer prevention, and anti-inflammatory activity[2].

Millet and sorghum are alternatives in areas where maize production is a challenge in terms of climate conditions such as in semi-arid areas. Sorghum and millet contribute to food and nutritional security at the household level[4]. Sorghum is highly adaptable to the changes brought about by climate change in Africa, thus its improved production can lead to an improvement in the food and nutrition status of nations in Sub-Saharan Africa[3]. Sorghum is resilient to the current and projected effects of climate change in Africa[5]. Sorghum survives low rainfalls and high temperatures. Climate change has been identified as one of the major contributors to food insecurity[2] whereas sorghum is a resilient crop in terms of floods, droughts, bareness, and salinity and it finds its use in the production of both food and livestock feeds[6].

A transition in the choice of food has been reported in Africa. There has been a decline in the consumption of millet and sorghum in Africa[7]. There has been a general decrease in the consumption of millet over the years from 1961 to 2013 for many Sub-Saharan African countries[8]. Millet has been classified as one of the under utilised and neglected foods, despite its drought resistance and nutritional properties[8]. Sorghum has been reported to be indigenous to Africa and smallholder farmers are the main producers of sorghum. The traditional varieties of sorghum are cultivated by African smallholder farmers despite there being little support in terms of policy and research initiatives towards sorghum[5].

The lagging behind of sorghum in terms of research, increased productivity, and policies that support its production has resulted in its underutilisation despite its resilience to harsh climatic conditions and drought. The factors that result in lower productivity and production of sorghum in smallholder farms should be addressed so that improved utilisation of sorghum can be realised in this era of the changing climate and the face of a decline of crop yields of many African staple foods[9]. There is a need for improvements in the varieties of sorghum seeds and improved extension programs to increase sorghum production in smallholder farms[2]. There is a need for serious interventions aimed at improving the production or consumption of millets[8]. Improvement of sorghum grains through research and innovation is significant in the promotion of the consumption of nutritious sorghum and production by smallholder farmers[5]. Technical support is crucial in terms of innovation and research to improve the productivity of underutilised and neglected crops like finger millet[10]. This passage has highlighted various areas that need to be addressed to improve the productivity and production of sorghum and millet. In other studies, challenges facing the production of cereals that is wheat production[11−15], maize production[16−19], and rice farming[20−22] have been addressed using interventions that are based on artificial intelligence. The objective of this paper is to explore the use of artificial intelligence in the production of millet and sorghum. The research hypothesises that artificial intelligence is used in the production of millet and sorghum. The application of artificial intelligence is significant as it helps to ascertain that millet and sorghum are also not neglected in terms of the use of advanced technology in their production.

Materials and methods

A Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach to carrying out a systematic review was conducted. Data was collected through the Google Scholar, Web of Science, and Scopus platforms. The search terms that were used are artificial intelligence and sorghum; machine learning and sorghum; artificial intelligence and millet; machine learning and millet. The exclusion criteria involved any small grains other than millet and sorghum. The identification and screening process is illustrated in Fig. 1.

Results

Sorghum and millet diseases and weeds

A Random Forest Classifier was used in the identification of sorghum diseases through the analysis of sorghum leaf images. Random forest was compared to multilayer perceptron (MLP) and support vector machine and it proved to be the best of the three. The F1 score for damaged sorghum was 0.99 whilst the F1 score for healthy sorghum was 0.988 indicating the accuracy of the Random Forest Classifier in sorghum disease identification. The F1 score for healthy sorghum was 0.963 and that for damaged sorghum was 0.992 using the support vector machine. The F1 score for healthy sorghum was 0.99 using the MLP[23]. This divulges that diseased sorghum can be accurately identified through the use of artificial intelligence applications. Deep Neural Networks (DNN) that utilize transfer learning can identify pearl millet mildew diseases with a precision of 90.5% and an accuracy of 95%. A smartphone can be utilized by farmers to the identification of pearl millet mildew disease using the proposed model of DNN with transfer learning[24]. The use of a smartphone integrated with artificial intelligence is an indication that even smallholder farmers can be equipped with such kind of technology that will enable them to identify diseases in millet in time. This will enable timeous responses from the farmers thereby addressing the problems that might have resulted in low yields or losses. Convolutional Neural Networks can distinguish between diseased sorghum and healthy sorghum through analysis of sorghum leaves[16].

Tadmare & Mahalakshmi[25] compared deep learning-based models in the identification of sorghum leaf diseases. These models are Alexnet and Google Net and they were used in the identification of the five common leaf diseases namely sooty stripe, gray leaf spot, zonate leaf spot, sorghum leaf blight, and leaf rust. Puig Garcia et al.[26] employed Unsupervised Machine learning to assess sorghum crop damage by white grubs. Crop damage by pests is costly in the food production chain. The sorghum fields were classified into three clusters depending on the severity of the insect damage and this was accomplished through the use of a K-means clustering algorithm after data collection using unmanned aerial vehicles. Roseline et al.[27] developed a model that can identify symptoms, use the symptoms in disease identification, and determine the severity of the disease of finger millets, and make recommendations using the fuzzy expert system. The development of different models for both millet and sorghum in the identification of diseases affecting sorghum and millet is significant in sorghum and millet crop management. The classification of the severity of the disease is also significant as it enables the correct remedy to be applied in line with the extent of damage to the crops.

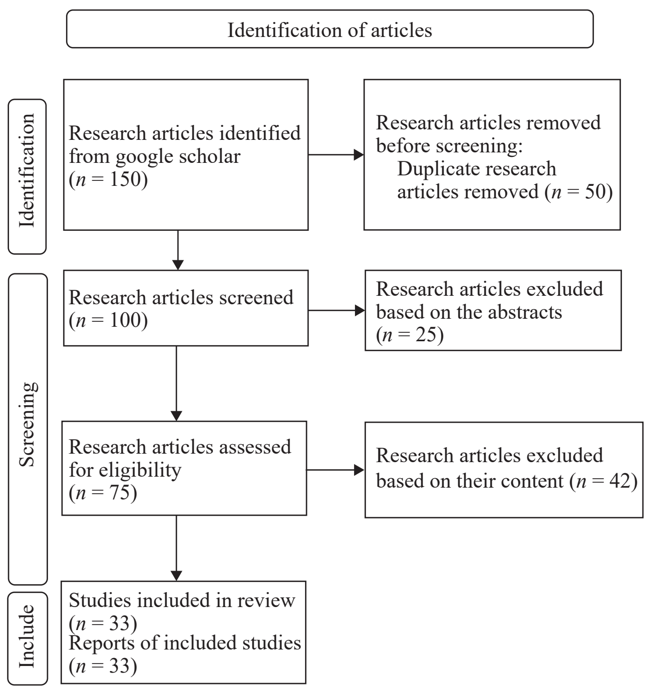

Fig. 1 Identification and screening of articles for review.

Unmanned aerial vehicles can be used to capture sorghum field images of intercrop weeds. Sorghum is then distinguished from the weeds through a residual neural network and deep learning with an F1 score greater than 89%, and this enables precise destruction of the weeds at their exact location. The developed model produced accurate results even under windy conditions that bring plants into motion making it difficult to capture clear images. The model developed is also very useful even in cases when plants overlap each other[28].

Climate change effects on sorghum and millet production

A genetic algorithm has been utilized to determine the future implications of climate change on pearl millet. The projected results were in 10-year periods ranging from 2017 to 2026, 2027 to 2036, and 2037 to 2047, and the results pointed to an approximately 12% decline in the yields of millet. This showed that even the small grains that are resilient to climate change are going to be greatly affected by an increase in mean temperatures in Punjab, Pakistan[29]. The climate change forecasting results assist in reflecting the need to develop future Climate Change Adaptation Strategies in millet production.

Small grain yield prediction

The forecasting of crop production plays a very significant goal towards attaining food security. It also enables farmers to plan effectively. Some traditional methods of predicting crop yields have some limitations and uncertainties hence the need to apply machine learning in the forecasting of crop production. Artificial intelligence simulates the functions of the biological brain[30]. A comparison of manual methods of measuring sorghum plant height and a digital image analysis-based model of determining sorghum node height were conducted. The digital analysis method is a non-destructive method of determining the biomass of sorghum and can be utilized at any stage of plant growth. The digital analysis method utilized Canopeo which quantifies the pixel number of green colour in the image which in turn relates to plant height according to the model. Any digital camera can be utilized to capture sorghum crop images. The method proved to be cheap and accurate[31]. Manual methods of counting sorghum heads are not accurate as they are prone to human error and are also time-consuming. A model that is based on deep learning employs test time augmentation to improve the counting of sorghum heads and it has proven to be effective as compared to individual transformed sets[32].

Factors that affect the growth of sorghum can be determined by artificial neural networks. A multilayer perceptron model built based on insecticides, crop yields, and temperature was developed and the effect of rainfall, temperature, and pesticides on sorghum yields was determined[30]. The number of heads of sorghum in a unit area is utilized in the determination of sorghum yield. Machine learning in the form of random forest can predict future sorghum yields under the effects of different irrigation treatments and the presence of different greenhouse gases. The artificial intelligence-based models made predictions from 2018–2099 using data from 1988 to 2016 for validation. The highest yield decline predicted was 8.2% and the lowest was 0.7% due to various climatic conditions of the regions of study[33]. The use of the You Only Looking Once model which utilizes a drone to capture sorghum images on the farm eliminates the need for physical inspection of the sorghum field when performing sorghum headcount[34]. A Time of Flight camera can be used in the detection of rows in sorghum fields through the navigation of under canopy. The same method was also used in the determination of rows in maize fields which indicates that technologies that are used in other crops can also be applicable in sorghum production[35].

Sorghum and millet seeds and cultivars

Red sorghum landraces were classified using AI-based linear discriminate analysis with an accuracy of 91.83% in a manner that is not destructive but fast and effective. An image analyzer was utilized to assess the images of red sorghum seeds based on the colour, shape, and size of the grain. The results assist in seed grain breeding for the red sorghum seeds[36]. Partial Least Squares Discriminant Analysis (PLS-DA) and Support Vector Machine can identify sorghum cultivars at an accuracy of 87% and this is significant in agriculture research and development activities. Ten different sorghum cultivars were successfully identified using AI-based models[37]. Kundu et al. developed a model centred on deep learning in the classification of millet seeds and it successfully categorized the seeds based on texture, colour and shape[38]. Before the flowering stage, sorghum and maize are difficult to distinguish due to their similarities and often a trained observer is employed to distinguish these. Trials were conducted to apply machine learning used in maize leaf detection to detect sorghum leaves using transfer learning. However, the detection for sorghum was a tenth less accurate than for maize[39]. It is interesting to note, this study revealed that the same machine learning that is applied in maize can also be applied in sorghum though there is a need for improvements to produce more accurate results for sorghum. These trials are significant as artificial intelligence takes less time to conduct a task as compared to trained observers. However, further studies should be conducted to improve the accuracy of artificial intelligence applications in the recognition of sorghum.

The adoption of improved sorghum varieties by smallholder farmers was established through the use of a deep learning neural network in Tanzania. This was necessary to determine the extent to which farmers were utilising the improved varieties of sorghum for better yields and productivity. The use of artificial intelligence yielded more accurate results as compared to the traditional ways of determining the extent of adoption of seed varieties[40]. This study shows that artificial intelligence is not only used in the identification of varieties but can also be extended to study how farmers are using different varieties of sorghum. The improved accuracy of artificial intelligence in the determination of the adoption of sorghum varieties is a significant result because more accurate results portray the true nature of the extent of use of improved varieties which in turn assist in decision-makers to the sorghum seed producers and policymakers.

Sorghum and millet irrigation

Machine learning was applied to identify sorghum grains that were affected by drought stress. The identification of drought-stressed sorghum grains was conducted by machine learning analysis of photographs that were taken by a 10-megapixel camera. The extent of the irrigation deficit was determined based on the sorghum grain images. Water stress affects the quality and yield of sorghum crops besides their resilience to a drought environment[41].

Land evaluation for sorghum and millet production

Evaluation of land for crop production is very significant as it determines the type of crop that should be cultivated under the evaluated land in a sustainable manner with high yields. For the evaluation to be conducted the services of a soil scientist are required at most and this might be costly to some farmers. The manual evaluation of land for crop production is also liable to some errors and takes longer than the use of artificial intelligence. Support Vector Machine (SVM), Parallel Random Forest (PRF), Linear Regression (LR), Gaussian Naive Bayesian (GNB), k-nearest neighbors algorithm KNN, and Linear Discriminant Analysis (LDA) were used in trials to determine the suitability of land for crop production. Accurate predictions of land evaluation were made in 1.7 s through the use of PRF in the analysis of soil properties without utilizing a soil science expert[42].

Land topography, climatic conditions, and soil characteristics were utilized as the basis for land evaluation for sorghum (*Sorghum bicolor* L. Moench) production. Geographic information systems which are based on fuzzy technology were used in the analysis and the results classified the land as not suitable (permanently), not suitable (currently), marginally suitable, and moderately suitable[43]. Trial-based comparisons of the use of Fuzzy Multi-criteria decision analysis methods and Boolean logic were conducted on the land evaluation for sorghum production based on mean temperatures, soil erosion, topography, and physical and chemical properties of soil. Both methods classified various land portions into regions but the Fuzzy Multi-criteria decision analysis methods classification was more detailed than that of the Boolean logic[44]. The suitability of land for millet and sorghum production can be determined by a fuzzy logic model based on soil texture, soil depth, soil drainage, soil chemical properties, soil fertility, land terrain, and irrigation sources. Land evaluation is significant in millet and sorghum production in the face of climate change[45].

Discussion

In this review, 33 articles were interrogated. The use of artificial intelligence in sorghum and millet production as highlighted above will be compared to the application of artificial intelligence in the production of other grain crops like maize in this discussion. The results of the use of various artificial intelligence-based models in the identification of diseases and weeds that affect sorghum and millet have been exhibited in the study. This is in line with a review[46] in which various artificial intelligence-based models were used in the identification of diseases affecting maize crops. The identification of weeds and diseases is important in sorghum and millet farming as it enables timely and accurate identification of weeds and diseases affecting the growth of the crops. This will in turn lead to a timely response thereby resulting in improved yields.

The results from the review also indicate that there is lagging in terms of the use of artificial intelligence in the prediction or forecasting of sorghum and millet in the face of climate change as only one article was reviewed in this paper. This is in contrast to maize production because the use of artificial intelligence in the prediction of the effects of climate change on maize production is shown in various studies[47−50].

The use of artificial intelligence in small grain yields production results from the review indicate that in some cases any type of camera can be used to capture images from the field which will then be utilized in the analysis for predictions. This is very important to smallholder farmers as they can use a readily available and affordable camera thereby making it affordable to them. The application of various models in the prediction of small grain yields is also an important point to note as this diversity brings a wider selection choice and allows for comparability of different artificial intelligent-based models in the prediction of small grain yields. Results on the use of artificial intelligence in the identification of small grain seeds concur with studies in which artificial intelligence was used in the identification of maize seeds[50−53].

In this review, only one article passed through the inclusion criteria and was assessed for millet and sorghum irrigation. In comparison to other crops in this instance maize it shows that sorghum and millet are lagging with regards to the use of artificial intelligence use in irrigation. Various artificial intelligence-based applications have been used in the management of the irrigation of maize[19,54−56]. A lot has to be done to apply artificial intelligence in the management of millet and sorghum irrigation so that with climate change irrigation can be applied to avoid water stress in millet and sorghum. Even though millet and sorghum are resilient they should not be left behind in the technological advancements.

The use of various artificial intelligent algorithms in the land evaluation for millet and sorghum production is impressive as this allows the proper selection of land for sorghum and millet production. It also ensures that the land preparation is done in line with the characteristics of the land. The use of artificial intelligence in land evaluation is very quick and accurate as outlined in the reviews and this ensures the gathering of all the relevant information in the shortest possible time as compared to when manual methods are utilized in the evaluation.

Conclusions

The results of the systematic review indicated that Artificial Intelligence techniques have been effectively utilized in sorghum and millet land evaluation, land preparation, cropping, disease, and weed management. It is conclusive that artificial intelligence can be applied in sorghum and millet production just like in any other grain crop. However, it is recommended that the use of artificial intelligence in irrigation management and prediction of the effects of climate change on sorghum and millet production should be intensified. It is recommended that artificial intelligence application developers should ensure that their applications cater to farmers at all levels from commercial farming to communal farming. It is also recommended that farmers should embrace artificial intelligence applications in millet and sorghum farming in different stages of crop production. Agricultural extension should also focus on awareness and demonstration of the use of artificial intelligence in sorghum and millet production to ensure its application by farmers in different regions, including rural communities.

Author contributions

The authors confirm contribution to the paper as follows: study conception and design: Kutyauripo I, Rushambwa M; data collection: Kutyauripo I, Rushambwa M; analysis and interpretation of results: Kutyauripo I, Rushambwa M, Palaniappan R; draft manuscript preparation: Kutyauripo I, Rushambwa M, Palaniappan R. All authors reviewed the results and approved the final version of the manuscript.

Data availability

All data generated or analyzed during this study are included in this published article.

Conflict of interest

The authors declare that they have no conflict of interest.

Dates

Received 31 July 2024; Revised 30 December 2024; Accepted 30 December 2024; Published online 20 February 2025

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