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Plant Seedlings Classification Using Deep Learning

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Abstract*: Agriculture is very important to human continued existence and remains a key driver of many economies worldwide, especially in underdeveloped and developing economies. There is an increasing demand for food and cash crops, due to the increasing in world population and the challenges enforced by climate modifications, there is an urgent need to increase plant production while reducing costs. Preceding instrument vision methods established for selective weeding have confronted with major challenges for trustworthy and precise weed recognition. In this paper, plant seedlings classification approach is presented with a dataset that contains approximately 5,000 images with 960 unique plants that belong to 12 species at a few developing phases. Convolutional Neural Network (CNN) algorithms, a deep learning technique extensively applied to image recognition was used, for this task. The results found that CNN-driven seedling classification applications when used in farming automation have the latent to enhance crop harvest and improve output and productivity when designed properly. The trained model achieved an accuracy of 99.48% on a held-out test set, demonstrating the feasibility of this approach.*

Keywords: Plant Seedlings, Classification, Deep Learning

1. Introduction

A seedling is a young plant sporophyte developing out of a plant embryo from a seed. Seedling development starts with germination of the seed. A typical young seedling consists of three main parts: the radicle (embryonic root), the hypocotyl (embryonic shoot), and the cotyledons (seed leaves). The two classes of flowering plants (angiosperms) are distinguished by their numbers of seed leaves: monocotyledons (monocots) have one blade-shaped cotyledon, whereas dicotyledons (dicots) possess two round cotyledons. Gymnosperms are more varied. For example, pine seedlings have up to eight cotyledons. The seedlings of some flowering plants have no cotyledons at all. These are said to be acotyledons [1,2].

The plumule is the part of a seed embryo that develops into the shoot bearing the first true leaves of a plant. In most seeds, for example the sunflower, the plumule is a small conical structure without any leaf structure. Growth of the plumule does not occur until the cotyledons have grown above ground. This is epigeal germination. However, in seeds such as the broad bean, a leaf structure is visible on the plumule in the seed. These seeds develop by the plumule growing up through the soil with the cotyledons remaining below the surface. This is known as hypogeal germination [3].

Growing plants continue to help as a source of nourishment and oxygen for all types of life on earth. Agriculture is main, proper automation of the agriculture process would aid in optimizing crop harvest and safeguard incessant productivity and sustainability. The makeover of the agricultural region by use of smart agricultural methods can influence economic growth in numerous countries. There is a strong relationship between increased productivity and economic affluence.

In this work, we show that a Deep Convolutional Neural Network (CNN) does well in classifying plant seedlings. In computer vision, CNNs have been known to be powerful visual models that yield hierarchies of features enabling accurate segmentation. They are also known to perform predictions relatively faster than other algorithms while maintaining competitive performance at the same time [6].

Deep Learning is an Artificial Intelligence (AI) subfield that imitates the works of a human brain in processing data and producing patterns for use in decision making. Deep learning is a subset of machine learning in artificial intelligence that has networks the skills of learning from data that is unlabeled or unstructured.

Deep Learning has grown hand-in-hand with the digital era, which has conveyed about an explosion of data in all forms and from every area of the world. This data, recognized as Big Data, is pinched from sources like social media, search engines, e-commerce platforms and more. This huge amount of data is freely accessible and can be shared through fintech applications like cloud computing. Though, the data, which normally is unstructured, is so massive that it could take years for humans to understand it and extract pertinent information. Companies understand the unbelievable potential that can result from disentanglement this wealth of information, and are progressively adapting to Artificial Intelligence systems for automated support [15-25].

One of the most common AI techniques used for processing Big Data is Machine Learning, a self-adaptive algorithm that gets gradually better analysis and patterns with experience or with new added data. If a digital payments company wanted to detect the occurrence of or potential for fraud in its system, it could use machine learning tools for this purpose.

The computational algorithm built into a computer model will process all transactions happening on the digital platform, find patterns in the data set and point out any anomaly detected by the pattern [26-40].

Deep learning, a division of machine learning, uses a hierarchical level of artificial neural networks to perform the process of machine learning. The artificial neural networks are constructed like the human brain, with neuron nodes linked together like a web. While traditional programs build to do analysis with data in a linear way, the hierarchical task of deep learning systems allows machines to process data with a nonlinear approach. A traditional approach to detecting fraud or money laundering might depend on the amount of transaction that precedes, while a deep learning nonlinear technique would include geographic, IP address, time, location, type of retailer and any other feature that is likely to indicate a fraudulent activity. The first layer of the neural network processes a raw data input like the amount of the transaction and send it on to the next layer as output. The second layer processes the previous layer's information by including extra information like the user's IP address and send on its result [41-60].

The next layer takes the second layer's information and includes raw data like geographic location and makes the machine's pattern even improved. This goes on across all levels of the neuron network.

Practical application of Deep Learning is fraud detection system. Using the fraud detection system mentioned above with machine learning, we can create a deep learning example. If the machine learning system created a model with parameters built around the amount of dollars a user sends or receives, the deep learning method can start building on the results offered by machine learning. Each layer of its neural network builds on its previous layer with added data like retailer, sender, user, social media event, credit score, IP address and a host of other features that may take years to connect together if processed by a human being. Deep learning algorithms are trained to not just create patterns from all transactions, but to also know when a pattern is signaling the need for a fraudulent investigation. The final layer relays a signal to an analyst who may freeze the user's account until all pending investigations are finalized [8].

Deep learning is used across all industries for a number of different tasks. Commercial apps that use image recognition, open source platforms with consumer recommendation apps and medical research tools that explore the possibility of reusing drugs for new ailments are a few of the examples of deep learning incorporation.

2. Related Work

The Authors in [9] used deep learning to detect five tomato leaves diseases. They achieved a high accuracy in detecting the tomato disease.

The authors in [10] provided a dataset that is aimed at ground-based weed or specie spotting and also suggested a benchmark measure to researchers to enable easy comparison of classification results. The authors in [12] demonstrated the effectiveness of a convolutional neural network to learn unsupervised feature representations for 44 different plant species with high accuracy.

In the course of exploring the right architecture for our model, we consider the work of [11] in classifying leaves using the VGGNet16 architectures. The authors in [13] implemented a 26-layer deep learning model consisting of 8 residual blocks in their classification of 10,000 images of 100 ornamental plant species achieving classification rates of up to 91.78%.

The authors in [14] addressed the problem of CNN-based semantic segmentation of crop fields separating sugar beet plants, weeds, and background solely based on RGB data by proposing a deep encoder-decoder CNN for semantic segmentation that is fed with a 14-channel image storing vegetation indexes and other information that in the past has been used to solve crop-weed classification.

3. Methodology

In this section we describe the proposed solution as selected convolutional network (ConvNet) architecture and discuss associated design choices and implementation aspects.

3.1 Dataset

The dataset used, provided by the Aarhus University Signal Processing group, in collaboration with University of Southern Denmark, contains a set of 5608 images of approximately 960 unique plants belonging to 12 species at several growth stages. See Fig. 1 for plant seedling samples.

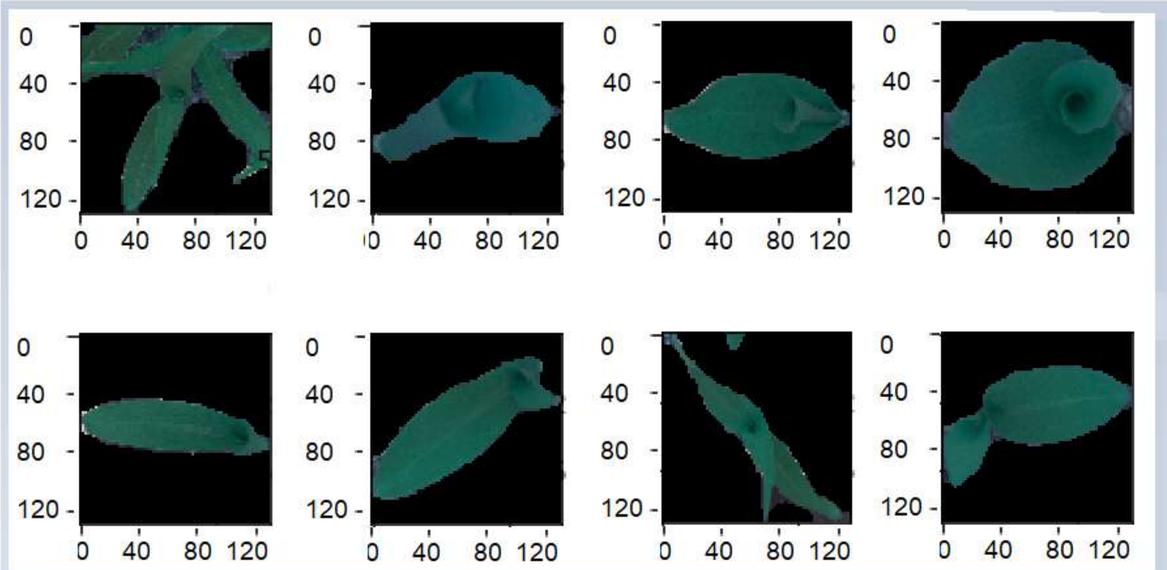

Figure 1: Images of the segmented plant seedling

3.2 Architecture

VGGNet is a well-documented and globally used architecture for convolutional neural networks [11]. This ConvNet became very widespread by accomplishing excellent performance on the ImageNet [12] dataset. It comes in several variations of which the two best-performing (with 16 and 19 weight layers) have been made publicly available. In this work, the VGG16 architecture was selected, since it has been shown to generalize well to other datasets. The input layer of the network expects a 224x224 pixel RGB image. The input image is passed through five convolutional blocks. Small convolutional filters with a receptive field of 3_3 are used. Each convolutional block includes a 2D convolution layer operation (the number of filters changes between blocks). All hidden layers are equipped with a ReLU (Rectified Linear Unit) as the activation function layer (nonlinearity operation) and include spatial pooling through use of a max-pooling layer. The network is concluded with a classifier block consisting of three Fully Connected (FC) layers.

3.3 Design considerations

The original VGG16 must be modified to suit the current solution: the final fully-connected output layer must perform 12 classes only.

3.3.1 Preprocessing

Input images must be preprocessed by:

- Normalizing the pixel values to a [0,1] range;
- Balance the 12 different species
  The current data is not balanced: (Fat Hen: 540, Small-flowered Cranesbill: 577, Maize: 257, Loose Silky-bent: 801, Sugar beet: 461, Common wheat: 255, Cleavers: 345, Common Chickweed: 713, Scentless Mayweed: 605, Black-grass: 330, Charlock: 451, Shepherds Purse: 273). We made the data balanced using augmentation by generating new images from the existing ones. After the balancing, the data became(Fat Hen: 801, Small-flowered Cranesbill: 801, Maize: 762, Loose Silky-bent: 801, Sugar beet: 801, Common wheat: 760, Cleavers: 801, Common Chickweed: 801, Scentless Mayweed: 801, Black-grass: 801, Charlock: 801, Shepherds Purse: 796) as seen in Fig.2 and Fig. 3.
- Resizing the image to be 128x128 pixels.

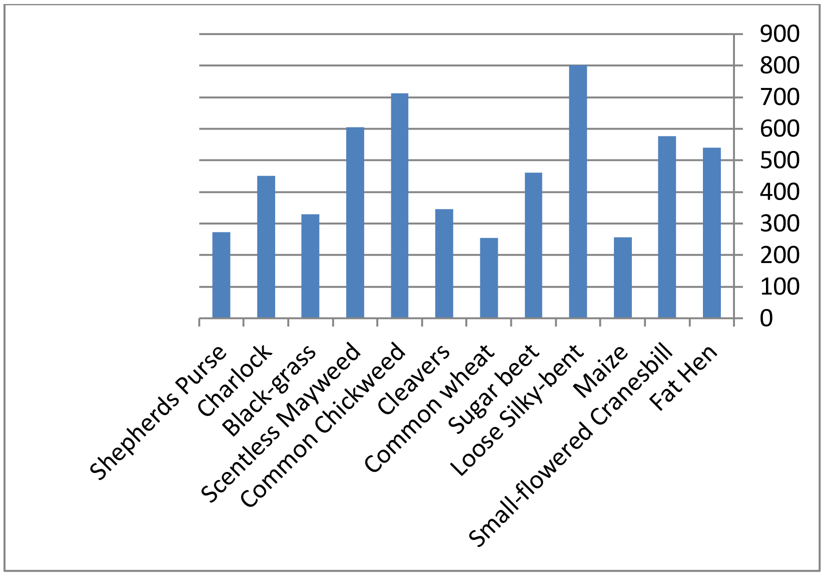

Figure 2: Bar graph showing the distribution of the different classes of plants before treatment

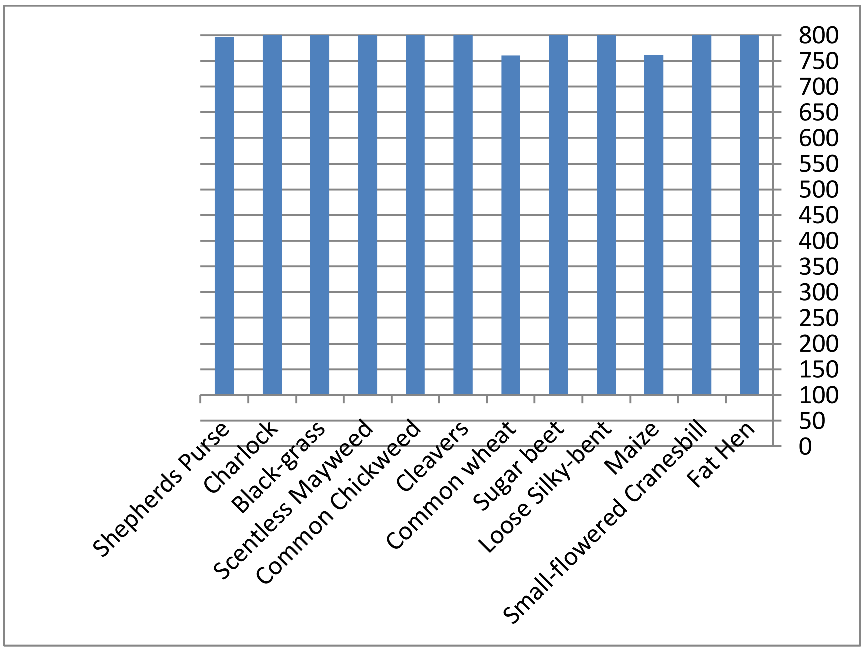

Figure 3: Bar graph showing the distribution of the different classes of plants after treatment

3.3.2 Data augmentation

In order to make the most of our few training examples and increase the accuracy of the model, we augmented the data via a number of random transformations. The selected data augmentation techniques were: size re-scaling, rotations of 40, horizontal shift, image zooming, and horizontal flipping.
Furthermore, it is expected that data augmentation should also help prevent overfitting (a common problem with small datasets, when the model, exposed to too few examples, learns patterns that do not generalize to new data) and, for this reason, improving the models ability to generalize.

3.4 One problem, three possible solutions

The modified VGG16 ConvNet can be used in three different ways:

- training the ConvNet from scratch;
- using the transfer learning paradigm to leverage features from a pre-trained VGG16 on a larger dataset; and
- keeping the transfer learning paradigm and fine-tuning the ConvNets architecture. These variants (named Method 1, Method 2, and Method 3, respectively) are described next.

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3.4.1 Training from scratch

The architecture is initialized with random weights and trained for a number of epochs. After each epoch, the model learns features from data and computes weights through backpropagation. This method is unlikely to produce the most accurate results if the dataset is not significantly large. However, it still can serve as a baseline for comparison against the two other methods.

3.4.2 ConvNet as feature extractor

Due to the relatively small number of images of plant seedling datasets, this method initializes the model with weights from the VGG16 trained on a larger dataset (such as ImageNet [11]), a process known as transfer learning. The underlying assumption behind transfer learning is that the pre-trained model has already learned features that might be useful for the classification task at hand.
This corresponds, in practice, to using selected layer(s) of the pre-trained ConvNet as a fixed feature extractor, which can be achieved by freezing all the convolutional blocks and only training the fully connected layers with the new dataset.

3.4.3 Fine-tuning the ConvNet

Another common transfer learning technique consists of not only retraining the classifier on the top of the network with the new dataset, but also applying a fine-tuning of the network by training only the higher-level portion of the convolutional layers and continuing the backpropagation.

In this work, we propose to freeze the lower level layers of the network because they contain more generic features of the dataset. We are interested in training only the top layers of the network due to their ability to perform extraction of more specific features. In this method, the first four convolutional layers in the final architecture are initialized with weights from the ImageNet dataset. The fifth, and final, convolutional block is initialized with weights saved and loaded from the corresponding convolutional layer in Method 1. This method was adapted in our current research.

4. Experiments and Discussions

We have done two experiments with Fine-tuning the ConvNet as described above.

- The first experiment: We used the original plant seedling dataset that consists of 5608 images after resizing the images to 128x128 pixels. We divided the data into training (90%), validation (10%). The training accuracy was 100% and the validation accuracy was 98.57%
- The second experiment: We used the balanced plant seedling dataset that consists of 9527 images after resizing the images to 128x128 pixels. We divided the data into training (90%), validation (10%). The training accuracy was 100% and the validation accuracy was 99.48%

We think that the more images we have the better the results will.

Figure 4: Training and validation accurcey

Figure 5: Training and validation Loss

5. Conclusion

We proposed a solution for assisting farmers to optimize crop. More specifically, we have designed and implemented a two-class classifier that takes plant seedling images with 12 different species an input, builds a model using deep learning convolutional neural networks, and uses this model to predict the type of (previously unseen) images of plant seedling.
The proposed approach achieves promising results – most notably, validation accuracy of 99.48% .

References

1. Brix, H. 1972. Growth response of Sitka spruce and white spruce seedlings to temperature and light intensity. Can. Dep. Environ., Can. For. Serv., Pacific For. Res. Centre, Victoria BC, Inf. Rep. BC-X-74. 17 p.
2. Pollard, D.F.W.; Logan, K.T. 1976. Prescription for the aerial environment for a plastic greenhouse nursery. p.181–191 *in* Proc. 12th Lake States For. Tree Improv. Conf. 1975. USDA, For. Serv., North Central For. Exp. Sta., St. Paul MN, Gen. Tech. Rep. NC-26.

3. Carlson, L.W. 1979. Guidelines for rearing containerized conifer seedlings in the prairie provinces. Can. Dep. Environ., Can. For. Serv., Edmonton AB, Inf. Rep. NOR-X-214. 62 p. (Cited in Nienstaedt and Zasada 1990).
4. Brown, K.; Higginbotham, K.O. 1986. Effects of carbon dioxide enrichment and nitrogen supply on growth of boreal tree seedlings. Tree Physiol. 2(1/3):223–232.
5. "Build with AI | DeepAI". DeepAI. Retrieved 2018-10-06.
6. Werbos, P.J. (1975). Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences.
7. Ng, Andrew; Dean, Jeff (2012). "Building High-level Features Using Large Scale Unsupervised Learning". arXiv:1112.6209[cs.LG].
8. Max A. Little, Patrick E. McSharry, Eric J. Hunter, Lorraine O. Ramig (2008), 'Suitability of dysphonia measurements for telemonitoring of Parkinson's disease', IEEE Transactions on Biomedical Engineering.
9. Ashqar, B. AM, & Abu-Naser, S. S. (2019). Image-Based Tomato Leaves Diseases Detection Using Deep Learning. International Journal of Academic Engineering Research (IJAER) 2 (12), 10-16.
10. T. Giselsson, R. Jørgensen, P. Jensen, M. Dyrmann, and H. Midtiby, A public image database for benchmark of plant seedling classification algorithms, CoRR, abs/1711.05458, 2017.
11. S. Lee, C. Chan, S. Mayo, and P. Remagnino, How deep learning extracts and learns leaf features for plant classification, Pattern Recognition, vol. 71, pp. 1-13, 2017.
12. Jeon, Wang-Su, and Sang-Yong Rhee, Plant leaf recognition using a convolution neural network, International Journal of Fuzzy Logic and Intelligent Systems 17, no. 1, pp 26-34. 2017.
13. Y. Sun, Y. Liu, G. Wang, and H. Zhang, Deep learning for plant identification in natural environment, Computational Intelligence and Neuroscience, 2017.
14. A. Milioto, P. Lottes, and C. Stachniss, Real-time semantic segmentation of crop and weed for precision agriculture robots leveraging background knowledge in CNNs, cs.CV, 2018. URL
15. Abu-Naser, S., Al-Masri, A., Sultan, Y. A., & Zaqout, I. (2011). A prototype decision support system for optimizing the effectiveness of elearning in educational institutions. International Journal of Data Mining & Knowledge Management Process (IJDKP), 1, 1-13.
16. Abu Naser, S., Zaqout, I., Ghosh, M. A., Atallah, R., & Alajrami, E. (2015). Predicting Student Performance Using Artificial Neural Network: in the Faculty of Engineering and Information Technology. International Journal of Hybrid Information Technology, 8(2), 221-228.
17. Elzamly, A., Abu Naser, S. S., Hussin, B., & Doheir, M. (2015). Predicting Software Analysis Process Risks Using Linear Stepwise Discriminant Analysis: Statistical Methods. Int. J. Adv. Inf. Sci. Technol, 38(38), 108-115.
18. Abu Naser, S. S. (2012). Predicting learners performance using artificial neural networks in linear programming intelligent tutoring system. International Journal of Artificial Intelligence & Applications, 3(2), 65.
19. Elzamly, A., Hussin, B., Abu Naser, S. S., Shibutani, T., & Doheir, M. (2017). Predicting Critical Cloud Computing Security Issues using Artificial Neural Network (ANNs) Algorithms in Banking Organizations. International Journal of Information Technology and Electrical Engineering, 6(2), 40-45.
20. Abu Naser, S. S., & Al-Bayed, M. H. (2016). Detecting Health Problems Related to Addiction of Video Game Playing Using an Expert System. World Wide Journal of Multidisciplinary Research and Development, 2(9), 7-12.
21. Abu Ghali, M. J., Mukhaimer, M. N., Abu Yousef, M. K., & Abu Naser, S. S. (2017). Expert System for Problems of Teeth and Gums. International Journal of Engineering and Information Systems (IJEAIS), 1(4), 198-206.
22. Abu Naser, S., & Akkila, A. N. (2008). A Proposed Expert System for Skin Diseases Diagnosis. INSInet Publication. Journal of Applied Sciences Research, 4(12), 1682-1693.
23. El Agha, M., Jarghon, A., & Abu Naser, S. S. (2017). Polymyalgia Rheumatic Expert System. International Journal of Engineering and Information Systems (IJEAIS), 1(4), 125-137.
24. Abu Naser, S., Al-Dahdooh, R., Mushtaha, A., & El-Naffar, M. (2010). Knowledge management in ESMDA: expert system for medical diagnostic assistance. AIML Journal, 10(1), 31-40.
25. Almurshidi, S. H., & Abu-Naser, S. S. (2018). EXPERT SYSTEM FOR DIAGNOSING BREAST CANCER. Al-Azhar University, Gaza, Palestine.
26. Abu Naser, S. S., & Alawar, M. W. (2016). An expert system for feeding problems in infants and children. International Journal of Medicine Research, 1(2), 79-82.
27. Al Rekhawi, H. A., Ayyad, A. A., & Abu Naser, S. S. (2017). Rickets Expert System Diagnoses and Treatment. International Journal of Engineering and Information Systems (IJEAIS), 1(4), 149-159.
28. Abu Naser, S. S., & AlDahdooh, R. M. (2016). Lower Back Pain Expert System Diagnosis and Treatment. Journal of Multidisciplinary Engineering Science Studies (JMESS), 2(4), 441-446.
29. Nabahin, A., Abou Eloun, A., & Abu Naser, S. S. (2017). Expert System for Hair Loss Diagnosis and Treatment. International Journal of Engineering

and Information Systems (IJEAIS), 1(4), 160-169.
30. Abu Naser, S. S., & Alhabbash, M. I. (2016). Male Infertility Expert system Diagnoses and Treatment. American Journal of Innovative Research and Applied Sciences, 2(4).
31. Qwaider, S. R., & Abu Naser, S. S. (2017). Expert System for Diagnosing Ankle Diseases. International Journal of Engineering and Information Systems (IJEAIS), 1(4), 89-101.
32. Abu Naser, S. S., & Al-Hanjori, M. M. (2016). An expert system for men genital problems diagnosis and treatment. International Journal of Medicine Research, 1(2), 83-86.
33. Naser, S. S. A., & Hasanein, H. A. A. (2016). Ear Diseases Diagnosis Expert System Using SL5 Object. World Wide Journal of Multidisciplinary Research and Development, 2(4), 41-47.
34. Nassr, M. S., & Abu Naser, S. S. (2018). Knowledge Based System for Diagnosing Pineapple Diseases. International Journal of Academic Pedagogical Research (IJAPR), 2(7), 12-19.
35. Abu Naser, S. S., & El-Najjar, A. E. A. (2016). An expert system for nausea and vomiting problems in infants and children. International Journal of Medicine Research, 1(2), 114-117.
36. Elqassas, R.,& Abu-Naser, S. S. (2018). Expert System for the Diagnosis of Mango Diseases. International Journal of Academic Engineering Research (IJAER) 2 (8), 10-18.
37. Naser, S. S. A., & Hilles, M. M. (2016). An expert system for shoulder problems using CLIPS. World Wide Journal of Multidisciplinary Research and Development, 2(5), 1-8.
38. Musleh, M. M., & Abu-Naser, S. S. (2018). Rule Based System for Diagnosing and Treating Potatoes Problems. International Journal of Academic Engineering Research (IJAER) 2 (8), 1-9.
39. Abu Naser, S. S., & Hamed, M. A. (2016). An Expert System for Mouth Problems in Infants and Children. Journal of Multidisciplinary Engineering Science Studies (JMESS), 2(4), 468-476.
40. Almadhoun, H., & Abu-Naser, S. (2017). Banana Knowledge Based System Diagnosis and Treatment. International Journal of Academic Pedagogical Research (IJAPR), 2(7), 1-11.
41. Abu Naser, S. S., & Mahdi, A. O. (2016). A proposed Expert System for Foot Diseases Diagnosis. American Journal of Innovative Research and Applied Sciences, 2(4), 155-168.
42. Dahouk, A. W., & Abu-Naser, S. S. (2018). A Proposed Knowledge Based System for Desktop PC Troubleshooting. International Journal of Academic Pedagogical Research (IJAPR) 2 (6), 1-8
43. Abu Naser, S. S., & Ola, A. Z. A. (2008). AN EXPERT SYSTEM FOR DIAGNOSING EYE DISEASES USING CLIPS. Journal of Theoretical & Applied Information Technology, 4(10).
44. Bakeer, H., & Abu-Naser, S. S. (2017). Photo Copier Maintenance Expert System V. 01 Using SL5 Object Language. International Journal of Engineering and Information Systems (IJEAIS) 1 (4), 116-124.
45. Abu Naser, S. S., & Shaath, M. Z. (2016). Expert system urination problems diagnosis. World Wide Journal of Multidisciplinary Research and Development, 2(5), 9-19.
46. Khella, R., & Abu-Naser, S. S. (2017). Rule Based System for Chest Pain in Infants and Children. International Journal of Engineering and Information Systems 1 (4), 138-148.
47. Abu-Naser, S. S., El-Hissi, H., Abu-Rass, M., & El-Khozondar, N. (2010). An expert system for endocrine diagnosis and treatments using JESS. Journal of Artificial Intelligence; Scialert, 3(4), 239-251.
48. Mrouf, A., Albatish, I., Mosa, M., & Abu Naser, S. S. (2017). Knowledge Based System for Long-term Abdominal Pain (Stomach Pain) Diagnosis and Treatment. International Journal of Engineering and Information Systems (IJEAIS) 1 (4), 71-88.
49. Abu Naser, S. S., Baraka, M. H.,& Baraka, A. R. (2008). A Proposed Expert System For Guiding Freshman Students In Selecting A Major In Al-Azhar University, Gaza.Journal of Theoretical & Applied Information Technology 4(9).
50. Abu-Nasser, B. S., & Abu-Naser, S. S. (2018). Cognitive System for Helping Farmers in Diagnosing Watermelon Diseases. International Journal of Academic Information Systems Research (IJAISR) 2 (7), 1-7.
51. Abu Naser, S. S., Alamawi, W. W., & Alfarra, M. F. (2016). Rule Based System for Diagnosing Wireless Connection Problems Using SL5 Object. International Journal of Information Technology and Electrical Engineering 5(6), 26-33.
52. Akkila, A. N., & Abu Naser, S. S. (2016). Proposed Expert System for Calculating Inheritance in Islam. World Wide Journal of Multidisciplinary Research and Development 2 (9), 38-48.
53. Abu Naser, S. S., & Zaqout, I. S. (2016). Knowledge-based systems that determine the appropriate students major: In the faculty of engineering and information technology, World Wide Journal of Multidisciplinary Research and Development 2 (10), 26-34.
54. AbuEl-Reesh, J. Y., & Abu Naser, S. S. (2017). A Knowledge Based System for Diagnosing Shortness of Breath in Infants and Children. International Journal of Engineering and Information Systems (IJEAIS) 1 (4), 102-115.
55. Abu Naser, S. S., & Bastami, B. G. (2016). A proposed rule based system for breasts cancer diagnosis. World Wide Journal of Multidisciplinary Research and Development 2 (5), 27-33.

56. Abu-Nasser, B. S. (2017). Medical Expert Systems Survey. International Journal of Engineering and Information Systems, 1(7), 218-224.
57. Abu Naser, S. S., & ALmursheidi, S. H. (2016). A Knowledge Based System for Neck Pain Diagnosis. World Wide Journal of Multidisciplinary Research and Development (WWJMRD), 2(4), 12-18.
58. Azaab, S., Abu Naser, S., & Sulisel, O. (2000). A proposed expert system for selecting exploratory factor analysis procedures. Journal of the College of Education 4 (2), 9-26.
59. Abu-Naser, S. S., Kashkash, K. A., & Fayyad, M. (2010). Developing an expert system for plant disease diagnosis. Journal of Artificial Intelligence, 3 (4), 269-276.
60. Barhoom, A. M., & Abu-Naser, S. S. (2018). Black Pepper Expert System. International Journal of Academic Information Systems Research, (IJAISR) 2 (8), 9-16.
61. AlZamily, J. Y., & Abu-Naser, S. S. (2018). A Cognitive System for Diagnosing Musa Acuminata Disorders. International Journal of Academic Information Systems Research, (IJAISR) 2 (8), 1-8.
62. Alajrami, M. A., & Abu-Naser, S. S. (2018). Onion Rule Based System for Disorders Diagnosis and Treatment. International Journal of Academic Pedagogical Research (IJAPR), 2 (8), 1-9.
63. Al-Shawwa, M., Al-Absi, A., Abu Hassanein, S., Abu Baraka, K., & Abu-Naser, S. S. (2018). Predicting Temperature and Humidity in the Surrounding Environment Using Artificial Neural Network. International Journal of Academic Pedagogical Research (IJAPR), 2(9), 1-6.
64. Salah, M., Altalla, K., Salah, A., & Abu-Naser, S. S. (2018). Predicting Medical Expenses Using Artificial Neural Network. International Journal of Engineering and Information Systems (IJEAIS), 2(20), 11-17.
65. Marouf, A., & Abu-Naser, S. S. (2018). Predicting Antibiotic Susceptibility Using Artificial Neural Network. International Journal of Academic Pedagogical Research (IJAPR), 2(10), 1-5.
66. Jamala, M. N., & Abu-Naser, S. S. (2018). Predicting MPG for Automobile Using Artificial Neural Network Analysis. International Journal of Academic Information Systems Research (IJAISR), 2(10), 5-21.
67. Kashf, D. W. A., Okasha, A. N., Sahyoun, N. A., El-Rabi, R. E., & Abu-Naser, S. S. (2018). Predicting DNA Lung Cancer using Artificial Neural Network. International Journal of Academic Pedagogical Research (IJAPR), 2(10), 6-13.
68. Al-Massri, R. Y., Al-Astel, Y., Ziadia, H., Mousa, D. K., & Abu-Naser, S. S. (2018). Classification Prediction of SBRCTs Cancers Using Artificial Neural Network. International Journal of Academic Engineering Research (IJAER), 2(11), 1-7.
69. Alghoul, A., Al Ajrami, S., Al Jarousha, G., Harb, G., & Abu-Naser, S. S. (2018). Email Classification Using Artificial Neural Network. International Journal of Academic Engineering Research (IJAER), 2(11), 8-14.
70. Metwally, N. F., AbuSharekh, E. K., & Abu-Naser, S. S. (2018). Diagnosis of Hepatitis Virus Using Artificial Neural Network. International Journal of Academic Pedagogical Research (IJAPR), 2(11), 1-7.
71. Heriz, H. H., Salah, H. M., Abu Abdu, S. B., El Sbihi, M. M., & Abu-Naser, S. S. (2018). English Alphabet Prediction Using Artificial Neural Networks. International Journal of Academic Pedagogical Research (IJAPR), 2(11), 8-14.
72. El_Jerjawi, N. S., & Abu-Naser, S. S. (2018). Diabetes Prediction Using Artificial Neural Network. International Journal of Advanced Science and Technology,124, 1-10.