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# Artificial Intelligence and its Application in Animal Disease Diagnosis

**Savleen Kour[1], Rajesh Agrawal[1], Neelesh Sharma[1*], Abha Tikoo[1], Nishi Pande[2] and Ayushi Sawhney[3]**

*[1]Division of Veterinary Medicine, Faculty of Veterinary Sciences & A.H., Sher-e-Kashmir University of Agricultural Sciences and Technology of Jammu, R.S. Pura, J & K, INDIA*
*[2]Division of Veterinary Gynaecology & Obstetrics, Faculty of Veterinary Sciences & A.H., Sher-e-Kashmir University of Agricultural Sciences and Technology of Jammu, R.S. Pura, J & K, INDIA*
*[3]Division of Veterinary Surgery & Radiology, Faculty of Veterinary Sciences & A.H., Sher-e-Kashmir University of Agricultural Sciences and Technology of Jammu, R.S. Pura, J & K, INDIA*

**Corresponding author: N Sharma; E-mail: drneelesh_sharma@yahoo.co.in*

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**ABSTRACT**

Present paper reviews about the origin, subfields, mandates and application of artificial intelligence in animal disease diagnosis. Artificial intelligence (AI) is intelligence manifested by machines and has developed into subfields; Machine and Deep learning. Machine learning (ML) provides application of algorithms for identification of patterns of data and creates a model to make future predictions. Commonly used algorithms are linear regression, random forest, decision tree, K-nearest and support vector machines. In deep learning, algorithms are classified into categories; Convolutional neural network, Restricted Boltzmann Machines, Auto encoder and Sparse Coding. The Convolutional Neural Networks (CNN) is one of the most notable approaches, doesn't require human supervision and automatically detects the significant features. Some of the commendable CNN architectures presented at ILSVRC **(**ImageNet Large Scale Visual Recognition Challenge (ILSVRC); AlexNet, ZFNet, VGG-16, GoogLeNet etc. Regarding use of AI technique in veterinary sciences, this paper reviewed some of the documented data of its application in disease prediction and diagnosis; The National Animal Disease Referral Expert System (NADRES) of ICAR-NIVEDI, detection of left atrial enlargement on canine thoracic radiology (Li *et al*., 2021), Predicting survivability and need for surgery in Horses with Colic (Fraiwan *et al.,* 2020), detection of sub clinical mastitis in cows with the help of machine learning by Ebrahimie *et al*. (2018), CNN (*GoogleNet)* in discriminating between meningiomas and gliomas in canines MRI's (Banzato *et al*., 2018) and using a xenograft platform and machine learning in development of exosomal gene to detect residual disease in dogs with osteosarcoma **(**Makielski *et al*., 2021).

**HIGHLIGHTS**

- Image-level diagnostics have been quite successful at employing CNN-based methods.
- Artificial Intelligence has wide scope in the disease diagnosis and farm management.

**Keywords:** Artificial learning, natural language processing, algorithms, deep learning, convolutional neural network

Artificial intelligence (AI) is intelligence manifested by machines, as opposed to the natural intelligence demonstrated by humans and animals. Machines mimic cognitive function associated with the human mind viz learning and problem assessment (Muthukrishnan *et al*., 2020). Artificial intelligence was invented as an academic discipline in 1959 and has tried many approaches during its lifetime. It includes brain stimulation, modeling human problem solving, logics, and databases of knowledge and imitation of human behaviour (Moran, 2007). Even after the establishment of AI as an academic discipline, it remains as non-significant scientific approach with

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limited practical application (Haenlein and Kaplan, 2019). The term Artificial Intelligence was stamped by John McCarthy (Crevier, 1993). The founders of AI were Allen Newell (CMU), Herbert Simon (CMU), John McCarthy (MIT), Marvin Minsky (MIT) and Arthur Samuel (IBM). Their students produced programmes that were describes as astonishing computers. They reportedly played better than average human, solved word problems in algebra and provided with logical theorems (Russell and Norvig, 2003). The founders of AI were optimistic and one of them; Herbert Simon believed that "machines will be capable, within twenty years of doing any work a man can do" (Simon, 1965). But, they failed to recognize the difficulty of some of the remaining tasks. The coming next years would be called as "AI winter" where functioning of research related AI was difficult due to difficulty in obtaining funds (Russell and Norvig, 2003). In 1980's, research on AI was revived by commercial success of expert systems in which stimulation of knowledge and analytical power of human experts was done. It gradually restored its authentication in late 90's and early 21$^{st}$ century by improving in functions like specific solution to problems related to logistics, data mining and medical diagnostics (Luger and Stubblefiled, 2004). Access to large number of data, algorithm improvements and faster programming of computers enabled advancement in machine learning. Machine learning and deep methods started to make a benchmark around 2010 (McKinsey & Company, 2017). The year 2015 was considered as a landmark year for artificial intelligence with increased number of software projects within Google that uses application of AI. There is increased demand of AI from sporadic usage in 2012 to current times based on its application (McKinsey & Company, 2017).

## Mandates of Artificial intelligence

- **Information representation and reasoning**: The Field of AI dedicated to represent information about the world in a language that can be utilised by computers to solve complex tasks (Hayes-Roth *et al*., 1983).
- **Planning and automated scheduling**: Unlike classical problems and their solutions, complex data must be discovered and optimised in multidimensional manner. For that AI planning/ scheduling is important and is concerned with the realization of strategies, sequences of action taken, execution by intelligent agents and autonomous robots (Malik, 2004).
- **Natural language processing (NLP)**: A subdivision of computer science, linguistics and AI which is concerned with interaction between human language and computer programming. They function in particular way to programme computers and processing of large amount of natural language data. Primary goal is making computer capable of understanding the contents of document presented. Then, it can accurately extract information from documents as well as categorization of the content themselves (Nadkarni *et al*., 2011).
- **Machine learning (ML)**: Process of study of computer algorithms that improve automatically through a large number of data and experience. It builds a model that utilises sample data, commonly referred as training data in order to make predictions without being explicitly biased to do so. Machine learning algorithms are used in a variety of applications such as in speech recognition, computer vision, email filtering and in medical field also, where it is unfeasible to develop conventional algorithm to do the needed task (El-Naqa *et al.*, 2015).
- **Machine perception:** Ability to use input information from detection sensors (such as microphones, cameras, wireless signals, sonar, radar and spectrum cameras) to deduce aspects of information in the world.

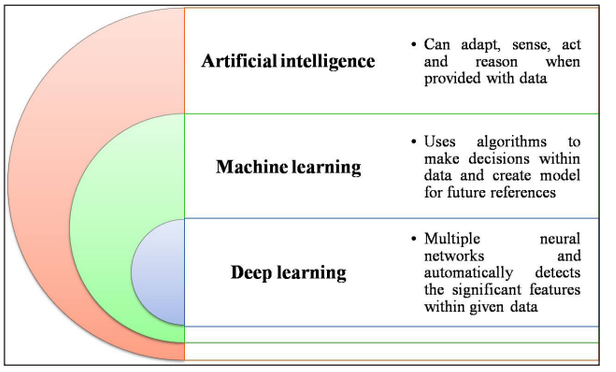


**Fig. 1:** Artificial intelligence and its subfield; Machine and Deep learning

**Machine learning and its functioning**

Machine learning (ML) is the process of utilising mathematical models of data to make computer learn without direct instruction given. With the application of algorithms, it helps in identification of patterns within the data and thus creates a model to make future predictions and decisions. With experience and provision of large number of data, accuracy in machine learning achieved. It requires human engineering and domain expertise to design information extractor that can transform raw data into suitable representation from which algorithm model can learn and detect patterns (El-Naqa *et al.,* 2015).

- **Supervised machine learning**: Algorithms make predictions based on a set of labelled examples from the past experience. It is useful when it's known what outcome should be. It helps learner to identify the similarities and differences when object to be classified have many variable qualities within their own domain and still have fundamental property which identifies them (Cherkassky and Mulier, 2007).
- **Unsupervised machine learning**: Algorithm allows machine to work on unlabelled data and discover pattern on its own that was previously undetected. It is useful when no information related to outcome is known (Cherkassky and Mulier, 2007).
- **Reinforcement learning:** Algorithms that learn from outcomes and decide which action to take next. Algorithm receives feedback that helps it to determine whether the choices it made were correct, indecisive or incorrect. Here a part of the data is labelled while other parts are unlabeled. In such case, the labelled one is used to provide aid in learning of unlabelled part. This kind of learning closely emulates with the development of skills by human and most of the processes in nature (Sutton and Barto, 1998).
- **Steps in machine learning**: The steps involved in machine learning; objective definition, collection of data, preparation of data, selection of algorithm, training of model, testing of model, prediction and then deployment of data (Kotsiantis *et al.*, 2007).

**Selection of algorithms in machine learning**

1. **Linear regression algorithm**: It comes under Supervised Learning technique, used for solving regression problems only. Helps in prediction of continuous dependent variable with the aid of independent variables. Primary goal is to find the best possible line that can predict accurately the outcome of continuous dependent variable. If single independent variable is utilised for prediction then it is termed as single linear regression whereas use of multiple variables form multiple linear regression. The algorithm establishes the best possible relationship between dependent and independent variables to make linear regression line (Bishop and Nasrabadi, 2006).
2. **Logistic analysis**: Logistic analysis is used to predict the dependent variable which is categorical in nature with the help of independent variables. Output of logistic regression lies between 0 to 1 only. Use of activation function (sigmoid function) to possibly weigh the sum of inputs and map the values between 0 and 1. Curve obtained in such function is known as sigmoid curve. This analysis is based on the Maximum likelihood estimation and according to it, the observed data should be most probable (Witten *et al*., 2016).
3. **Decision tree algorithm**: Decision Tree algorithm is a kind of supervised learning technique used for classification and regression problems, preferably used for classification. It is represented as tree-based classifier in which internal nodes represent features of dataset, branches depict the decision rule and each leaf node presents the outcome. The decision node used to make decision and have multiple branches whereas leaf nodes are outputs of those decisions and have no further branches. It represents all the possible outcomes of a problem graphically, based on the given conditions (Charbuty and Abdulazeez, 2021).
4. **Random forest algorithm**: One of the popular machine learning algorithm which belongs supervised learning technique. Represents both the classification and regression problems in machine learning, based on concept of ensemble learning in which multiple classifiers combines to solve complex set of data and meanwhile improves the performance of the model. It

contains number of decision tree of various subsets of given complex data and takes the average to enhance the accuracy of predictive model. Instead of single decision tree, it relies on multiple trees and takes prediction from each based on majority outcomes therefore predicts the final output (Ren *et al*., 2017).

5. **Support vector algorithm**: Popular algorithm of supervised learning technique used for regression and classification problems. Main goal is to create a decision boundary that can separate n-dimensional space into subsets that can be easily put by new data point in future in correct category. This decision boundary is called as hyperplane and vector machine selects the extreme vectors which creates these hyperplane. The extreme vectors are known as support vectors and therefore, the algorithm is coined as Support Vector machine (Somvanshi *et al*., 2016).
6. **K-nearest algorithm**: Is an Unsupervised Learning algorithm, which groups the unlabeled dataset into numerable different clusters. Each cluster is associated with a centroid. The main aim is to minimise the sum of distances between data point and their corresponding clusters. It performs mainly two functions; determination of best values for K points/centroids by an intrusive/repeated process and assigning each data points to its nearest centroid (those points nearest to particular k-centre creates a cluster) (Zhang, 2016).

## Understanding of Deep learning and its principle of functioning

DL (Deep learning) is a promising subfield of machine learning, composed of multiple layers, uses raw data as input, and improves the representations of data. DL in which a machine is fed with raw data and develops its own representations needed for pattern recognition. Composed of multiple layers of representation and are typically arranged sequentially. They are composed of a large number of nonlinear, primitive operations in which raw data is put into representation layer in the beginning and later is fed onto next layers, transforming into abstract like representation (Bordes *et al*., 2012).

Deep learning algorithms are classified into categories; Convolutional neural network, Restricted Boltzmann Machines, Auto encoder and Sparse Coding.

**Convolutional neural network**: The Convolutional Neural Networks (CNN) is one of the most notable approaches in deep learning in which multiple layers are trained in a manner that has been found very (LeCun *et al*., 1998). It's a type of deep-learning algorithm which is designed to process information that doesn't exhibits natural spatial variance (e.g., visuals; whose meaning doesn't change during translation). It doesn't require human supervision, automatically detects the significant features within given data (Alzubaidi *et al*., 2021). In ImageNet Large Scale Visual Recognition Challenge (ILSVRC), the most popular CNN architectures were proposed by top competitors. ImageNet is a project that aims to develop a widespread database of visual information that can be used by researchers in the field of object identification and recognition. AlexNet was the first known model to improve image classification programme considerably, with an error rate of 16.4% using the ImageNet dataset. Whereas, VGG16 considered as preferred choice for extracting features from images by the majority of researchers in visual recognition pattern community (Monshi *et al*., 2020).

**Table 1:** ILSVRC winners of CNN architectures

| Winner by Year | Convolutional layers | Error rate | Reference |
|---|---|---|---|
| 2012 - AlexNet | 8 | 16.4 | Krizhevsky *et al*., 2012 |
| 2013 - ZFNet | 8 | 11.7 | Zeiler *et al*, 2014 |
| 2014 second - VGG-16 | 16 | 7.4 | Simonyan and Zisserman, 2014 |
| 2014 first - GoogLeNet | 22 | 6.67 | Szegedy *et al*., 2015 |
| 2015 - ResNet | 152 | 3.57 | He *et al*., 2016 |
| 2016 second– ResNeXt | 101 | 3.03 | Xie *et al*., 2017 |
| 2016 – CUImage Team | 152 | 2.99 | Tweedale, 2018 |
| 2017 - SENet | 152 | 2.25 | Hu *et al*., 2018 |

Generally, a CNN consists of main neural layers, which are convolutional layers, pooling layers, and fully connected layers.

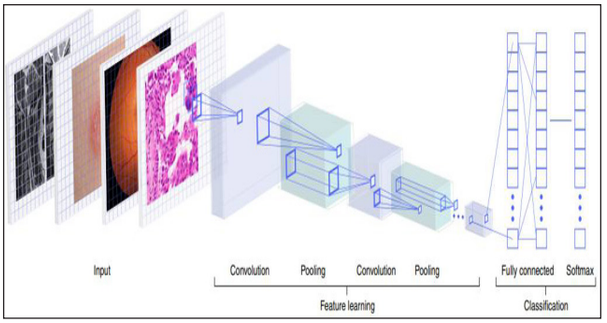


**Fig. 2:** Convolutional neural network architecture (Esteva *et al.,* 2019)

**Convolutional layer**: It comprises of convolutional filters, also known as a kernels**.** Input image as N-dimensional entity is convolved through these filters to generate an output featured map (Alzubaidi *et al.,* 2021).

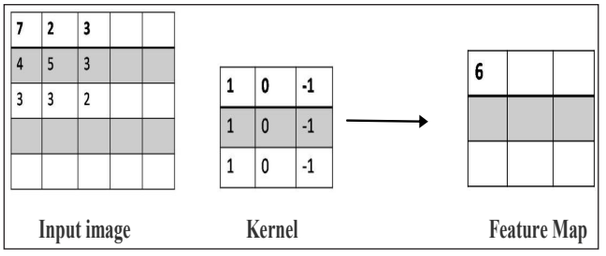


**Fig. 3:** Generation of Feature map in convolutional layer

**Pooling layer:** A pooling layers follows convolutional layer which is used to reduce the dimensions of featured map. Just like convolutional layers, pooling layer is invariant to translation as they take neighbouring pixels to account for computations. Maximum and average pooling are the most commonly used practices as they operate upon each feature map separately to generate a new set of pooled feature map (Scherer *et al*., 2010).

- ❒ It focuses on assuring exclusively the correct location of the feature.
- ❒ It makes the representation of featured map approximately invariant to small translations.
- ❒ Therefore, it is aimed to preserve the detected features in smaller representation by discarding data which is less significant at the cost of spatial representation (Boureau *et al*., 2010).

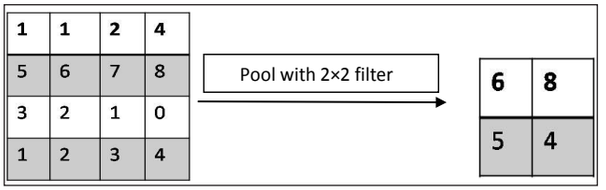


**Fig. 4:** Maximum pooling method

**Activation number:** The mapping of input to output is in no-linear fashion and this process is attained by activation layers; moreover it gives CNN the ability to learn complicated databases on its own without human supervision. Ability to differentiate and error back propagation to train the network are significant features of activation number. It's an element-wise operation over the input volume and therefore the input and the output are identical in dimensions. Main function is to add non-linearity in the networks to make it capable of complex and learning data. Without it, neural networks are just linear regression models. Types of activation numbers are Sigmoid, tanH, Relu and Softmax (Dhureja and Pahwa, 2019). ReLu is most commonly used, ranges from 0 to infinity (Lin and Shen, 2018). Softmax produces multiple output for an input array (Wu *et al*., 2016).

**Fully connected layer:** This layer is located at the end of each CNN architecture. The so-called fully connected (FC) approach where each neuron is connected to all the neurons of previous layer is present. It is utilised as CNN classifier.

## Application of AI in veterinary sciences

The National Animal Disease Referral Expert System (NADRES) of ICAR-NIVEDI is a system that works on combining and coordinating the alert and response mechanisms for the stake holders in prediction, prevention and control of animal disease threats (zoonotic ones also) through sharing of data, epidemiological studies and filed missions to asses and prevent outbreak, whenever needed. Combining livestock disease data and Artificial Intelligence techniques provide new opportunities to prevent outbreak and maintenance in the animal healthcare sector. From all the 31 AICRP centres, disease outbreak data is collected and is maintained in NADRES v2 (National Animal Disease Referral Expert System version 2). Two regression models, Generalized Linear Models

(GLM) and Generalized Additive Models (GAM) and six machine learning algorithms, i.e. Random Forest (RF), Boosted Regression Tree (BRT), Artificial Neural Network (ANN), Multiple Adaptive Regression Spline (MARS), Flexible Discriminant Analysis (FDA) and Classification Tree Analysis (CTA) are used for disease modelling. The outcome of best fitted model/s were categorised into 6 risk levels-No risk (NR), Very low risk (VLR), Low risk (LR), Moderate risk (MR), High risk (HR) and Very high risk (VHR).

Application of artificial intelligence for detecting left atrial enlargement on canine thoracic radiology (Li *et al*., 2021). Medical records of canine patients who had thoracic radiographic examination and echocardiograph performed within 72 hours of X-ray from 2010-2017 were screened. Those images were categorised echocardiographically positive or negative for left atrial enlargement. The DICOM images of right lateral thoracic radiograph were obtained as jpeg files. These images were resized as matrix of 64 × 64 pixels. The first images (711; 90%) in chronological order were designated as training dataset. The remaining 10% of total data were used as testing models. Images for training purpose were split into 10 subsets of equal size to train deep learning algorithms in CNN. Each training subset was sequentially used as validating dataset for cross validation. After cross validation, data obtained were used for evaluation of predicting performance of remaining 10% of testing dataset images with prediction results from average of 10 models. The sensitivity of the model was 68.42% and specificity of 87.09% with overall accuracy of CNN was 82.71%. Prediction from accuracy of CNN model was compared with the findings and performance of radiologists. An agreement was there with CNN model and radiologist findings in 69 of 81 cases resulting in 85% congruence.

Predicting survivability likelihood and need for surgery in Horses presented with acute abdomen pain (Colic) with use of Artificial intelligence (Fraiwan *et al.,* 2020). Medical records of horses (n=285) presented with signs of abdominal pain (colic) with attributes like sex, gender, abdominal pain, nasogastric reflux, response to analgesia, rectal findings, rectal examination, heart rate and abdominocentesis were included. Machine learning system uses one of the four algorithms: Naive Bayes, Random forest, and Multilayer Perceptron**.** Random forest classifier gave highest accuracy with an average of 76% and a maximum of 87.7%. Highest average precision of 97.4% was achieved by Naive Bayes classifier. Whether the horse needs surgery or not, its correctly identified by the accuracy of the algorithms. Whereas, number of horses correctly predicted for need of surgery to the total number that was predicted as needing surgery is represented by precision of algorithm.

Machine learning algorithm for diagnosis of chronic Hypoadrenocortism in dogs (Raegen *et al*., 2019). During the period of 2010-2017, medical records of all the dogs with rsting cortisol level were obtained. Study of blood count and serum chemistry, one week cortisol level measured with exclusion criteria viz; hyperadrenocorticism, corticosteroids, therapy with trilostane, mitotane, or ketoconazole were done. In cases and control group, medical record (signalment, cortisol concentrations before and after ACTH stimulation test) were included. The post-ACTH level after stimulation test was >2 mg/dl in control groups. These patients were sub-categorised as normal Na:K ratio (>27) or low ratio (<27). The training set comprised of 80% of data and 20% of set aside as test model. Machine learning classification used here in this case was based on decision tree. Standard reference values of ACTH stimulation test was used to compare accuracy, sensitivity and specificity of algorithm for the identification of CHA positive cases. A sensitivity of 99.5% and specificity of 99.4% at the optimal cut point were obtained when all cases (test and traninig) were classified by the algorithm.

Subclinical mastitis causes long term reduction in the milk yield and is most important form of mastitis economically (Ruegg, 2003). Animals having mCMT score of <2 are categorised as sub-clinical mastitis with no apparent change in milk composition and clinical signs (Zul-i-Huma *et al*., 2020). Meta-analysis of cow-basis prevalence of subclinical mastitis was carried out by Bangar *et al*. (2015) using data of 6344 cows from 25 studies. The pooled cow-basis prevalence of subclinical mastitis was found to be 46.35% (95 % CI 39.38; 53.46). As documented by Ebrahimie *et al*. (2018), detection of sub clinical mastitis in cows with the help of machine learning was done. A total of eight variables from milk samples viz; volume, fat, protein, lactose, EC, milking time, peak flow and somatic cell count were taken to account. The somatic cell count was considered as output variable and other variables as dependent inputs when dataset imported into rapid miner

software (RapidMiner). Based on several input features or variables (electrical conductivity, volume, lactose, milking time, fat, protein and peak flow), decision tree models create a classification model that predicts the value of output variable (somatic cell count). Lactose being on the top of decision tree model played a key role in determination of pattern of mastitis. All the cows (100%) with low levels of lactose (<4.5 g/dl) and volume (<21.7l) had mastitis and a strong pattern for sub-clinical mastitis in milking data was identified by decision tree random forest models.

Convolutional neural networks (CNNs) (i.e. a class of deep learning) were used to count reticulocytes in cat blood images. They achieved a high accuracy of 98.7% (Vinicki *et al*., 2018).

Deep convolutional neural network (CNN, *GoogleNet)* in discriminating between meningiomas and gliomas in canines MRI images, with accuracy of 94% (Banzato *et al*., 2018).

Using a novel xenograft platform and machine learning, development of an exosomal gene signature to detect residual disease in dogs with osteosarcoma was done by Makielski *et al*. (2021). The major hurdle in development of effective therapies against osteosarcoma is because of lack of specefic biomarkers to treat and predict the risk. Extracellular microvesicles secreting exosomes emerge as powerful diagnostic tools. Makielski *et al*. (2021) developed a method using canine osteosarcoma in xenografts of mouse to differentiate the tumor-derived from host-response exosomal mRNAs (messenger RNA). This model allows characterisation of osteosarcoma-specefic gene signatures by RNA sequencing and bioinformatics pipeline of species differentiation. Total of five gene (*SKA2, NEU1, PAF1, PSMG2, and NOB1*) were validated in dogs with spontaneous osteosarcoma by qRT-PCR (quantitative real time reverse transcription PCR), whereas, machine learning model classified dogs into diseased or healthy groups. Serum/plasma exosomes were extracted from 53 dogs in different clinical groups viz; healthy, osteosarcoma, other bone tumor, or non-neoplastic disease. Training set from pre-treatment osteosarcoma were used and post-treatment sample for validation set was considered and classified as "osteosarcoma detected" or. Dogs had longer remission period, upto 15 months after treatment whose post-treatment samples were classified "osteosarcoma not detected".

**Limitations of artificial intelligence**

Major limitations of application of artificial intelligence in diagnosis and treatment includes; lack of reliable reporting system requiring tens of millions of image/ text samples which are not readily available, samples are structured with scattered an non-uniform information that did not help in facilitation in the learning process of deep learning models, most of the models require labelled data for supervised learning and manual labelling of data is a task of difficulties (Anwar *et al*., 2018), at individual level, work is not done and coordination with engineers and skilled labour is required (Esteva *et al.,* 2019). For this, major efforts are required from the information technology industry to achieve desired efficacy, accuracy and cost effective. Laboratories and health centres need to work in harmony to progress the implementation and utilisation of electronic health records (Esteva *et al.,* 2019).

## CONCLUSION

Image-level diagnostics have been quite successful at employing CNN-based methods. Deep-learning models have achieved physician-level accuracy at a broad variety of diagnostic tasks. AI can assist physicians by providing up-to-date medical information from journals, textbooks and clinical practices to inform proper patient care. Machine learning also plays a role in phenotype prediction from genetic data, disease risk, forecast of epidemic and pandemic (Esteva *et al.,* 2019). A neural network, known as COVNet, examine 4,300 CT scans and accurately distinguish between patients with COVID-19 and other community-acquired pneumonia and lung diseases (Singh *et al.,* 2021). Sofie is the most advanced veterinary medical search tool available. Sofie uses IBM Watson Technology® to search its vast knowledge base of over 40,000 pages of peer-reviewed, evidence-based reference materials from the top veterinary textbooks, journals, and conference proceedings (Sandhya *et al*., 2020).

We reviewed in detail the origin, goals and the basics of artificial intelligence with information regarding components of machine and deep learning; keeping in mind about its motives in health care sector particularly in veterinary science. In today's time, due to the rise of Big Data and improvements in computing power, AI has entered the professional and public conversation. In near future, AI will be increasingly be part of our day to day

routine raises a question of its requirement and if so, in which form.

## REFERENCES


Alzubaidi, L., Zhang, J., Humaidi, A.J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M.A., Al-Amidie, M. and Farhan, L. 2021. Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *J. Big Data*, **8**(1): 1-74.

Anwar, S.M., Majid, M., Qayyum, A., Awais, M., Alnowami, M. and Khan, M.K. 2018. Medical Image Analysis using Convolutional Neural Networks: A Review. *J. Med. Syst.,* **42**(11): 1-13.

Bangar, Y.C., Singh, B., Dohare, A.K. and Verma, M.R. 2015. A systematic review and meta-analysis of prevalence of subclinical mastitis in dairy cows in India. *Trop. Anim. Health Prod.*, **47**(2): 291-297.

Banzato, T., Bernardini, M., Cherubini, G.B. and Zotti, A. 2018. A methodological approach for deep learning to distinguish between meningiomas and gliomas on canine MR-images. *BMC Vet. Res.*, **14**(1): 1-6.

Bishop, C.M. 2006. Pattern recognition and machine learning. 1st Ed., Springer, Singapore, pp. 137- 178.

Bordes, A., Glorot, X., Weston, J. and Bengio, Y. 2012. Joint learning of words and meaning representations for open-text semantic parsing. *In:* Proceedings of the 15th International Conference on Artificial Intelligence and Statistics (AISTATS). Mar, 2012. La Palma, Canary Islands, pp. 127-135.

Boureau, Y.L., Ponce, J. and LeCun, Y. 2010. A theoretical analysis of feature pooling in visual recognition. *In:* Proceedings of the 27th International Conference on Machine Learning. Jun, 2010. Haifa, Israel, pp. 111-118.

Boureau, Y.L., Ponce, J. and LeCun, Y. 2010. A theoretical analysis of feature pooling in visual recognition. *In:* Proceedings of the 27th International Conference on Machine Learning. Jun, 2010. Haifa, Israel, pp. 111-118.

Charbuty, B. and Abdulazeez, A. 2021. Classification based on decision tree algorithm for machine learning. *JASTT*, **2**(1): 20-28.

Cherkassky, V.S. and Mulier, F. 2007. Learning from data: concepts, theory, and methods. 2nd Ed., IEEE Press/Wiley-Interscience, Hoboken, New Jersey, USA, pp. 177-248.

Crevier, D. 1993. AI: the tumultuous history of the search for artificial intelligence. 1st Ed., Basic Books, New York, USA, pp. 26-50.

Dureja, A. and Pahwa, P. 2019. Analysis of non-linear activation functions for classification tasks using convolutional neural networks. *Recent Pat. Comput. Sci.*, **12**(3): 156-161.

Ebrahimie, E., Ebrahimi, F., Ebrahimi, M., Tomlinson, S. and Petrovski, K.R. 2018. Hierarchical pattern recognition in milking parameters predicts mastitis prevalence. *Comput. Electron. Agric.,* **147**: 6–11.

El-Naqa, I. and Murphy, M.J. 2015. What is machine learning?. *In:* Machine learning in radiation oncology. El-Naqa, I.,Li, R. and Murphy, M.J., 1st Edn., Springer, Cham, London, pp. 3-11.

Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., Corrado, G., Thrun, S. and Dean, J. 2019. A guide to deep learning in healthcare. *Nat. med.*, **25**(1): 24-29.

Fraiwan, M.A. and Abutarbush, S.M. 2020. Using artificial intelligence to predict survivability likelihood and need for surgery in horses presented with acute abdomen (colic). *J. Equine Vet. Sci.*, **90**: 102973.

Fuentes, S., Gonzalez-Viejo, C., Cullen, B., Tongson, E., Chauhan, S.S. and Dunshea, F.R. 2020. Artificial intelligence applied to a robotic dairy farm to model milk productivity and quality based on cow data and daily environmental parameters. *Sensors*, **20**(10): 2975.

Haenlein, M. and Kaplan, A. 2019. A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *Calif. Manage. Rev.*, **61(**4): 5-14.

Hayes-Roth, F., Waterman, D.A. and Lenat, D.B. 1983. Building expert systems. 1st Ed., Addison-Wesley Longman, Boston, USA, pp. 6-7.

He, K., Zhang, X., Ren, S. and Sun, J. 2016. Deep residual learning for image recognition. *In:* Proceedings of the IEEE conference on computer vision and pattern recognition. Dec, 2016, Las Vegas, NV, USA. pp. 770-778.

Hu, J., Shen, L. and Sun, G. 2018. Squeeze-and-excitation networks. In Proceedings of the IEEE conference on computer vision and pattern recognition. Jun, 2018, Salt Lake City, UT, USA. pp. 7132-7141.

Huma, Z.I., Sharma, N., Touqeer, A., Kour, S. and Pathak, A.K. 2020. Alteration in the hemato-biochemical profile of mastitis affected lactating dairy cattle. *Rumin. Sci.,* **9**(1): 33-36.

Tweedale, J.W. 2018. An application of transfer learning for maritime vision processing using machine learning. *In:* International Conference on Intelligent Decision Technologies. June, 2018, Springer, Cham, pp. 87-97.

Kotsiantis, S.B., Zaharakis, I. and Pintelas, P. 2007. Supervised machine learning: A review of classification techniques. *In:* Emerging artificial intelligence applications in computer engineering, Maglogiannis, I., Karpouzis, K.,Wallace, B.A. and Soldatos, J. 1st Ed., IOS Press, USA, pp. 3-24.

Krizhevsky, A., Sutskever, I. and Hinton, G.E. 2012. Imagenet classification with deep convolutional neural networks. *In:*

Advances in neural information processing systems. Dec, 2012. Lake Tahoe, Nevada, pp. 1-9.

LeCun, Y., Bottou, L., Bengio, Y. and Haffner, P. 1998. Gradient-based learning applied to document recognition. *In:* Proceedings of Institute of Electrical and Electronics Engineers, 28th Annual Frontiers in Education Conference: Moving from "teacher-centered" to "learner-centered" education. Nov, 1998. Tempe, AZ, USA. pp. 2278-2324.

Li, S., Wang, Z., Visser, L.C., Wisner, E.R. and Cheng, H. 2020. Pilot study: application of artificial intelligence for detecting left atrial enlargement on canine thoracic radiographs. *Vet. Radiol. Ultrasound.*, **61**(6): 611-618.

Lin, G. and Shen, W. 2018. Research on convolutional neural network based on improved Relu piecewise activation function. *Procedia Comput.*, **131**: 977-984.

Luger, G. and Stubblefield, W. 2004. *Artificial Intelligence: Structures and Strategies for Complex Problem Solving. 5th Ed., Addison-Wesley* Longman, Boston, USA, pp. 928.

Makielski, K.M., Donnelly, A.J., Khammanivong, A., Scott, M.C., Ortiz, A.R., Galvan, D.C., Tomiyasu, H., Amaya, C., Ward, K.A., Montoya, A. and Garbe, J.R. 2021. Development of an exosomal gene signature to detect residual disease in dogs with osteosarcoma using a novel xenograft platform and machine learning. *Lab. Invest.*, **101**(12): 1585-1596.

Malik, O.P. 2004. Amalgamation of adaptive control and AI techniques: applications to generator excitation control. *Annu. Rev. Control.*, **28**(1): 97-106.

McKinsey & Company. 2017. "Ask the AI experts: What's driving today's progress in AI?". Available at https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/ask-the-ai-experts-whats-driving-todays-progress-in-ai.

Monshi, M.M.A., Poon, J. and Chung, V. 2020. Deep learning in generating radiology reports: A survey. *Artif. Intell. Med.*, **106**: 101878.

Moran, M.E. 2007. Evolution of robotic arms. *J. Robot.*, **1(**2): 103-111.

Muthukrishnan, N., Maleki, F., Ovens, K., Reinhold, C., Forghani, B. and Forghani, R. 2020. Brief history of artificial intelligence. *Neuroimaging Clin. N. Am.*, **30**(4): 393-399.

Nadkarni, P.M., Ohno-Machado, L. and Chapman, W.W. 2011. Natural language processing: an introduction. *JAMIA.*, **18**(5): 544-551.

Reagan, K.L., Reagan, B.A. and Gilor, C. 2020. Machine learning algorithm as a diagnostic tool for hypoadrenocorticism in dogs. *Domset.*, **72**: 106396.

Ren, Q., Cheng, H. and Han, H. 2017. Research on machine learning framework based on random forest algorithm. *In:* American Institute of Physics Conference Proceedings. Mar, 2017. Wuhan, China, pp. 1-7.

Ruegg, P.L. 2003. Investigation of mastitis problems on farms. *Vet. Clin. North Am. Food Anim. Pract.*, **19**(1): 47-73.

Russell, S.J. and Norvig, P. 2003. Artificial Intelligence: A Modern Approach. *2nd Ed., Prentice Hall, New Jersey, USA,* pp. 16-18.

Sandhya, P., Mujumdar, A.M. and Biswas, A. 2020. Cognitive Computing and Its Applications. *In:* Analyzing Future Applications of AI, Sensors, and Robotics in Society. Musiolik, T.H. and Cheok, A.D., 1st Ed., IGI Global, Pennsylvania, United States, pp. 47-68.

Scherer, D., Müller, A. and Behnke, S. 2010. Evaluation of pooling operations in convolutional architectures for object recognition. In International conference on artificial neural networks. Springer, Berlin, Heidelberg, pp. 92-101.

Simon, H.A. *1965.* The Shape of Automation for Men and Management. *1st Ed., Harper & Row, New York.*

Simonyan, K. and Zisserman, A. 2014. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:*1409.1556.

Singh, S., Biwalkar, A. and Vazirani, V. 2021. Clinical Decision Support Systems and Computational Intelligence for Healthcare Industries. *In:* Knowledge Modelling and Big Data Analytics in Healthcare: Advances and Applications. Mehta, M., Passi, K., Chatterjee, I. and Patel, R., 1st Edn., CRC Press, Florida, United States, pp. 37-64.

Somvanshi, M., Chavan, P., Tambade, S. and Shinde, S.V. 2016. A review of machine learning techniques using decision tree and support vector machine. *In:* Second International conference on computing communication control and automation. Aug, 2016. Pune, India, pp. 1-7.

Sutton, R.S. and Barto, A.G. 1998. Reinforcement learning: an introduction. 1st Ed., MIT Press, Cambridge, Massachusetts, pp. 2-15.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V. and Rabinovich, A. 2015. Going deeper with convolutions. *In:* Proceedings of the IEEE conference on computer vision and pattern recognition. Oct, 2015. Boston, MA, USA. pp. 1-9.

Vinicki, K., Ferrari, P., Belic, M. and Turk, R. 2018. Using convolutional neural networks for determining reticulocyte percentage in cats. *arXiv preprint arXiv:*1803.04873.

Witten, I.H., Frank, E., Hall, M.A. and Pal, C.J. 2016. Data mining: Practical machine learning tools and techniques. 4th Ed., Morgan Kaufmann Publishers, San Francisco, USA. pp. 125-129.

Wu, Y., Li, J., Kong, Y. and Fu, Y. 2016. Deep convolutional neural network with independent softmax for large scale face

recognition. In: Proceedings of the 24th ACM international conference on Multimedia. Oct, 2016. Amsterdam, The Netherlands, pp. 1063-1067.

Xie, S., Girshick, R., Dollár, P., Tu, Z. and He, K. 2017. Aggregated residual transformations for deep neural networks. *In:* Proceedings of the 30th IEEE conference on computer vision and pattern recognition. Jul, 2017. Honolulu, Hawaii, USA. pp. 1492-1500.

Zeiler, M.D. and Fergus, R. 2014. Visualizing and understanding convolutional networks. *In:* Proceedings of the 13th European Conference on Computer Vision. Sep, 2014. Zurich, Switzerland. pp. 818-833.

Zhang, Z. 2016. Introduction to machine learning: k-nearest neighbours. *Ann. Transl. Med.,* **4**(11): 218.