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Analysing Deep Learning and Machine learning Model for Cattle Recognition

Amanpreet Kaur

Department of Computer Science and Applications, Guru Nanak College, Sri Muktsar Sahib, Punjab, INDIA

Abstract:
In machine learning, feature extraction is a very important step in the construction of any pattern classification that extracts relevant features to identify the class from group of images. To recognizing object, accuracy depends upon the quality of features extracted from an image. Unique feature extraction has high accuracy in recognizing classes. In Deep learning image recognition is based on such as strong feature extraction ability and high recognition accuracy. In this paper we have discussed all the approaches used to recognize cattle from traditional to deep learning approaches, we have also analyzed the comparison of machine and deep learning approaches. We tried to explore few models of deep learning and its architecture that may result with high accuracy.

Keywords: Alex NET, LeNET, YOLO, Machine Learning, Deep Learning

1. Introduction

The cattle livestock resources are required to be managed as it plays essential role in agricultural production and rural economy development. It is also important for the breed selection and protection. To improve the overall working efficiency of livestock resources, we need to accurately identify individual cattle, its health issues, behavioural issues, and growth tracking. To develop such system, we need to promote advance machine learning technologies for livestock production. There are many promising studies to classify cattle based on human observation, traditional methods for identification, machine learning and deep neural networks.

The first approach of studies is totally based on the human observation that is time consuming and may not be accurate and burdensome for cattle farmers. The second approach is based on traditional methods classified into: Permanent Identification method (PIM), Semi-Permanent Identification (SIM) and Temporary Identification method (TIM). PIM includes ear notches, ear tattoos, hot ironing and freezing [Stanford *et al.*,2001]. These methods require very close examination, physically harm cattle, disease transmission. SIM categorized as ID collars, Ear Tags [Hilpert, 2003], these methods are not feasible as it loses it efficacy, effect physical growth of cattle and causes conflicts if multiple ear tags or ID collars are installed so it effects accuracy of cattle identification system. TIM is classified into Sketching/ painting and RFID (Radio frequency identification system). These methodologies are not reliable due to security concerns, cost effectiveness and technological implications such as short range, hacking, and tempering.

The third approach is based on machine learning models that extract features using feature extraction algorithm from the sample image of cattle to manage livestock in the farms. This methodology is based on the computer vision that extract feature from the distinct biometric features of the cattle. Biometric feature extraction traits are retinal vascular pattern. Allen *et al.,* 2008, have established a retinal image for identification but these images are difficult to capture and has problems like poor retinal images not properly identified. Lahiri *et al.,* 2011 developed system to identify based on coat patterns of animals but such system is not suitable for single colour breed. The accuracy achieved by the system is 85.0%. Noviyanto and Arymurthy, 2012 established muzzle pattern from images of cattle for identification of system using beads and ridges as Region of Interest (ROI) for identification using SURF (Speeded up robust feature) feature extraction approach. Chen *et al.,* 2013 have propose iris analysis for identification of cattle based on rings, furrows, crypts, corona, freckles, and fibres. Techniques implemented for identification are Local intensity variation, empirical model and fractal dimension. Cai and Li, 2013 have focused on facial feature of cattle for identification of cattle using local binary descriptor to trace the cattle in the field with 95.30% identification accuracy. Li *et al.,* 2017 developed cattle identification based on tail head images as Region of Interest (ROI) using LDA (Linear discriminant analysis) and SVM (Support Vector Machine) classification techniques. Kaur *et al.,* 2023 proposed Holistic features extraction SIFT (Scale Invariant Feature Transform), SURF (Speeded up Robust Feature), and ORB (Oriented Fast and Rotated BRIEF), to carry out experimental work and achieved 97.23% accuracy.

The fourth approach for cattle identification is based on the deep neural networks, this approach has very promising results for detection of cattle, its behaviour, cattle recognition, cattle health issues based on image analysis. Andrew *et al.*, 2019 identified from coat patterns of moving cattle based on CNN (Convolutional neural networks) architecture, it implemented Yolov2, and achieved accuracy of 94.40%. Bello *et al.* ,2020, recognized cattle from coat patterns on a dataset composed of 1000 images. CNN for training and testing of input images and it achieves accuracy of 89.95%. Chen *et al.,*2021 emphasised on identifying black-colored Angus breed. The authors implemented three models of neural network (NN) namely; ResNet50, PrimNet, and VGG16. This system achieved good accuracy with VGG16 net of 85.45%. Shojaeipour *et al.* ,2021 focus on YOLOv3 and ResNet50, CNN algorithm to detect and extract cattle muzzle regions in images. Here, they achieved a high accuracy of 99.11% with the SoftMax classifier. Hao *et al.,* (2023) proposes mutual attention learning (Bottle neck attention module, Convolutional Block attention Module, Triplet Attention Module) methods for identification of individual Jinnan Cattle breed in china to manage livestock resources. Zhang *et al.,*2023 proposes YOLOX to locate pattern, DeepOstu to binarize body pattern and EfficientNet-B1 model for classification that attained 98.50% of accuracy.

2. Comparison of machine learning and deep learning models

This study has identified the cattle using machine learning (ML) models and Deep learning (DL) models from scholarly databases is presented in Table 1, these models exhibit promising accuracy. It has been evaluated from survey report that ML models for cattle identification are SVM (Support vector machine), KNN (k-nearest Neighbour) and ANN (Artificial Neural Network). In machine learning distinct features considered were SIFT, SURF, LBP, Harris corner detector and Shi-Tomasi. DL models are CNN (Convolutional Neural Network), ResNet inception (Residual Network), PrimNET (Pretraining Network) and YOLO (You only look once).

Approaches	Total Images	Methods	Accuracy	References
Machine Learning	2266 images	Retinal images using optibrand	98.3%	Allen *et al.,* 2008
	120 images	CO-1+ Joint Stripes of coat patterns, Distance algorithm	85.00%	Lahiri *et al.,* 2011

	80 images	SURF	90.6%	Noviyanto and Arymurthy, 2012
	300 images	Local Binary Descriptor	95.30%	Cai and Li, 2013
	298 images	LDA and ANN SVM Classification	99.70%	Li *et al.,* 2017
	930 images	SIFT, SURF, ORB & K-NN, Decision Tree and Random Forest classifier	97.23%	Kaur *et al.,*2023
Deep Learning	1039 images	CNN, Yolov2	94.40%	Andrew *et al.,* 2019
	1000 images	Neural Network with Convolutional Layers	89.95%	Bello *et al.* ,2020
	1047 Images	ResNet50, PrimNet, and VGG16	85.45%	Chen *et al.,*2021
	2900 images	YOLOv3 and ResNet50	99.11%	Shojaeipour *et al.* ,2021
	37011 images	Mutual attention learning model using	98.91%	Hao *et al.,* (2023)
	1180 images	YOLOX	98.50%	Zhang *et al.,* (2023)

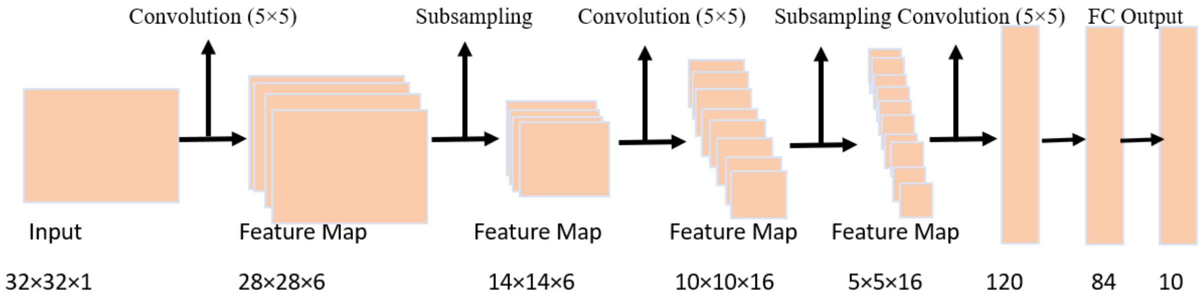
Table 1: A Comparison of machine learning models and deep learning models

3. Convolutional Neural Network in Deep Learning.

Convolutional Neural Network is deep learning algorithm suited for object recognition, object classification, detection, and image segmentation. CNN performs its task in multiple layers namely convolutional layers, pooling layers, and fully connected layers. In convolutional layers filters are applied to the input image that extracts features such as edges, textures, shapes, lines, circle, gradients, and even facial features. Pooling layers accepts output from convolutional layer and retain the important features by reducing spatial dimensions. Later, output is passed to next layer that is fully connected to classify the images. CNN model does not require image preprocessing. It is a multilayered feed forward neural network assembled with multiple grouping and hidden layers. There are numerous types of CNN models: LeNet, AlexNet, ResNet, VGG, YOLOX, YOLOv3.

1. LeNet

Lenet, a CNN architecture developed by LeCun, Y. (1989) was a successful image recognition model for handwritten digit recognition. This architecture includes two set of convolutional, pooling layers followed by subsampling layers and three fully connected layers as represented in Figure 1. The first convolutional layer uses the kernel 5×5 and it implements 6 filters to the input image, then it reduces the features of feature map with spatial dimension. In the second convolutional layer with kernel size of 5×5 and 16 filters are applied to first pooling layers followed by subsampling layer. The output of this is passed to next fully connected layer with neurons of 120,84 and 10 respectively, this layer is used for classification with distribution values of 10 digits.



*FC: Fully connected layer

Figure 1: Architecture of LeNet

Input Layer: It is the first layer of LeNET that receives input in the form of images and then pass it to next layer of network model.
Convolutional Layer: This layer applies filters to output of input layer that act as an input of this layer that is responsible for learning features.
Pooling Layer: This layer increases the invariance by reducing spatial dimensions. LeNET has two pooling layers for more specified data.

2. AlexNET

This architecture is for image recognition and classification, this algorithm works on huge dataset of labelled images and it attains very good accuracy on visual recognition tasks Krizhevsky *et al.*, This model consists of 8 layers with weights distributed as 5 Convolutional layers and 3 fully connected layers. Each layer has ReLu activation function (Rectified Linear Unit) performed for nonlinearity. The input to this model is RGB images. The convolutional layers extract the edges of the images and fully connected layer learn these features that are extracted. These models could be trained faster using saturation activation function such as tanh or sigmoid. AlexNET model reduce the problem of overfitting by using data augmentation and dropout method as it has two dropout layers. Dropout is implemented in the first two fully connected layers. The output size of convolution layer is measured using equation

output= ((Input-filter size)/ stride) +1 (*equation 1*)

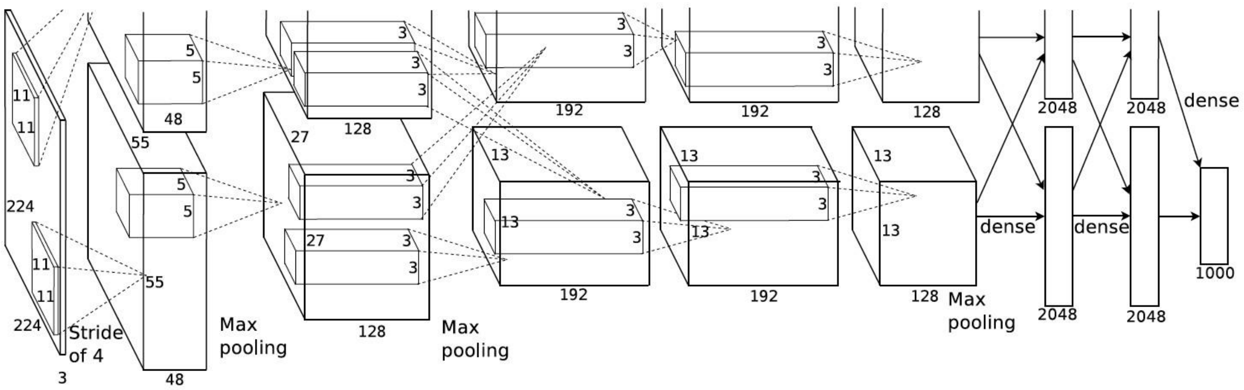


Figure 2: Architecture of AlexNET

Max-pooling is a feature embedded in convolutional layer applied after the first, second, and fifth layer. It accumulates features from maps with filter on image. This pooling layer reduce the number of parameters to learn. The kernels of the second, fourth, and fifth convolutional layers are connected only to those kernel maps in the previous layer as represented in Figure 2. The kernels of the third convolutional layer are connected to all kernel maps in the second layer. The neurons in the fully connected layers are connected to all neurons in the previous layer.

3. YOLO (You look only once)

YOLO is an object detection algorithm in deep learning Redmon *et al*., (2017). This model is different from other models as it performs in real time environment and have more accurate predictions. Speed of YOLO is very fast as it processes the images at 45 frames per second. Its detection accuracy is also high with minimal error.

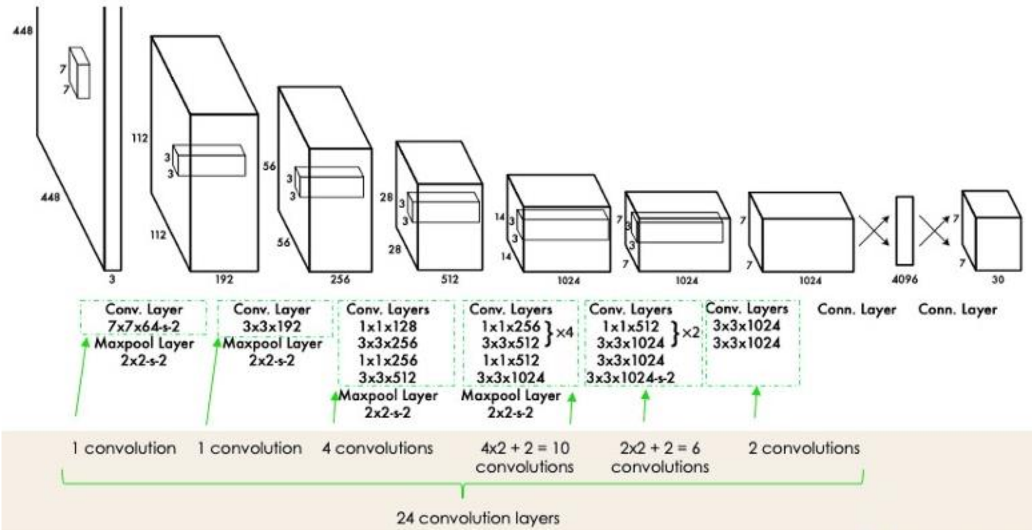


Figure 3: Architecture of YOLO

Working of YOLO architecture is represented in Figure 3. It resizes the input image into 448×448 before forwarding to convolutional network. A 1×1 convolution is first applied to reduce the number of channels, which is then followed by a 3×3 convolution to generate a cuboidal output. It uses the ReLU activation function It prevents the problem of overfitting with techniques like dropout and batch normalization.

4. Challenges in research directions

The reviewed article represents different types of challenges faced by author are Quality database: Using approaches like ML and DL requires quality of database for cattle identification. It has been discussed in review that images are blurred, illuminated variance, noisy images and of low quality due to continuous movement of cattle. Even as the images are collected from outside/indoor farm environment are affected. The collected database requires to be normalized and cropped to reduce the size of image for data processing Kumar *et al.,*2017. In DL large and quality data set is required for efficient result, to train the DL models video dataset is used in several studies chen *et al*, 2021 and data is augmented to enhance the performance of system. Benchmark Dataset: Lack of benchmark dataset is not available in public domain to extract the features for cattle identification, and to calculate the performance of ML and DL models. Duration and image overlapping: Dataset is collected at different duration (day and night) with distinct environment for training and testing. While collection of databases few images are overlapped with another animal, images are not able to properly segmented. Feature selection: Most of the articles reviewed have stated that dataset collected for the images are smaller, so efficient and large feature extraction is not possible. Feature selection is implemented on large feature set. Bias and Variance in machine learning: Bias occurs when leaning algorithm do not capture the underlying complexity of data in database. Chances of error may be due to model inability. These inabilities are as input feature used in to train and test data lead to inaccuracy and are unfit model. The size of database is not as required by the model or features are not properly scaled and have noises. Variance is if models perform good on training but results low on testing data that indicates overfitting. Overfitting problems are sorted with cross validation, ensemble and data augmentation. Such models are highly biased and has low variance. Complexity of model: in model architecture, we need to adjust the parameters and weights that increases the complexity of ML and DL models. Some times the model becomes too complex as it tends to overfit the training dataset and such system requires to reduce model performance on test dataset. Cost effective: DL Models are cost effective than ML models, it requires large amount of dataset and its performance depends upon complexity of the model. Cost is affected by the vision-based system. Cattle identification is difficult if cattle are kept in open environment where cheap network system is required to transfer images back to server that needs Internet of Things (IoT) technology.

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