DeepCattle: A Deep Learning Framework for Automated Detection and Severity Assessment of Ocular Squamous Cell Carcinoma in Cattle

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Abstract. In this artificial intelligence era, health care plays vigorous role in day today life. The disease caused to the cattle's are pink eye, new forest disease are caused by infectious Bovine Keratoconjuctivitis (IBK) and cancer eye are caused by Ocular Squamous Cell Carcinoma (OSCC) disease which are often found in young calf where these bacterial diseases spread easily through the transmitter such as flies, etc., The cow suffers more through this disease such as tear straining on the eyes, pains and irritation are exposed due to sunlight. These diseases are not accurately identified through naked eyes where diagnosing at earlier stage will prevent the cattle from the loss of its life. Eyes of the cattle's are major representation to classify whether the significant cow is infected or not through these disease.Ocular squamous cell carcinoma is a critical ocular disease affecting young calves, which can lead to severe health complications when it is left untreated. The deep learning-based approach for the early detection and classification of OSCC is to identify an early-stage OSCC lesions and assess disease severity. The model leverages a Convolutional Neural Network combined with a Bidirectional Long Short Term Memory to classify ocular images and to determine disease progression. Experimental results demonstrate that the proposed model achieves an accuracy of 93% when applied to high-resolution ocular images, significantly enhancing diagnostic efficiency and supporting timely clinical decision-making.

Keywords: Ocular Squamous Cell Carcinoma, Convolutional Neural Network, Gated Recurrent Unit.

1 Introduction

Ocular squamous cell carcinoma (OSCC), commonly referred to as "cancer eye," a prevalent and aggressive neoplasm affects the ocular and peri-ocular regions of cattle, particularly in breeds with un-pigmented eyelids such as Herefords. The etiology of OSCC is multifactorial, with significant risk factors including prolonged exposure to ultraviolet (UV) radiation and lack of eyelid pigmentation. Ocular Squamous Cell Carcinoma (OSCC) is a highly malignant tumor that originates from the squamous epithelial cells of the ocular region that typically affects the conjunctiva, sclera and cornea of the cattle. Many recent studies have identified the genetic components contributing to OSCC susceptibility, for an instance equine squamous cell carcinoma has pointed to a

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variant in the UV damage DNA repair gene DDB2, suggesting a potential genetic predisposition that could be analogous in bovine cases. The chronic exposure to ultraviolet (UV) radiation is one of the primary risk factors where it causes DNA damage in the cells of the eye, particularly in regions like the conjunctiva and cornea

1.1 Problem Statement

The Cattle suffer significantly from the Ocular squamous cell carcinoma (OSCC) diseases that cause symptoms such as tear staining around the eyes, pain, and irritation, especially when exposed to sunlight. These conditions are often difficult to detect with the naked eye, OSCC can lead to severe health consequences, underscoring the importance of timely identification and intervention

1.2 Motivation

Traditional detection methods are often time-consuming and require expert intervention, thereby limiting opportunities for early diagnosis and timely treatment. The eyes of cattle play a vital role in determining whether the calf is infected, as they provide visible signs of potential illness.

1.3 Objective

The main objective is to identify early-stage OSCC lesions and assess disease severity to prevent the calf and the proposed system helps the care taker to know about the disease. So that the affected individual calf can be separated from the other cattle from the infection.

2 Literature Survey

Genetic factors also play a crucial role in OSCC susceptibility. Research indicates that cattle with less periocular pigmentation are at a heightened risk, as pigmentation offers protection against harmful UV rays. An ocular squamous cell carcinoma (OSCC) in cattle was reviewed on focusing its epidemiology, diagnostic challenges, and management where genetic factor such as cattle with less periocular pigmentation was focused to protect the cattle's from uv rays [1]. The deep learning model with the application of artificial intelligence were proposed to diagnose a veterinary image [2]. An electronic health records are maintained using deep learning which were be scalable and accurate [3]. A comprehensive review was conducted on the medical image with respect to the human and veterinary using deep learning technique [4]. Convolutional neural network was used to classify an ocular image from the veterinary medical image [5]. Transfer learning technique with deep learning model was used to detect the cancer from the veterinary ophthalmology [6]. The various deep learning approaches were used to diagnose the both clinical and field settings [7]. An image based diagnostic system was used in veterinary medicine, focusing on the use of deep learning and AI [8]. The study focuses on deep learning model for detecting ocular squamous cell carcinoma (OSCC) in animals, specifically focusing on the veterinary field [9]. The system explores the use of deep learning for the early detection of ocular lesions in cattle. The study underscores the potential of AI in improving early diagnosis of ocular conditions that might otherwise go unnoticed, leading to timely intervention and better outcomes for the animals. The research illustrates how DNNs can be trained to recognize patterns in ocular images that are indicative of disease, thus assisting veterinarians in diagnosing and treating cattle more effectively. [10].

The advancements in deep learning for diagnostic imaging in veterinary medicine where it discuss how deep learning algorithms, particularly CNNs, are transforming the way veterinary professionals interpret diagnostic images such as radiographs, CT scans, and ultrasounds [11] The study investigates the use of deep convolutional neural networks (CNNs) for the early detection of diseases in cattle where deep learning can assist in identifying early signs of disease in cattle, using data from a variety of sources, including images and health records. An AI can support preventative care, reduce disease outbreaks, and improve cattle health management, offering a valuable tool for farmers and veterinarians in improving livestock health monitoring [12].

These references collectively represent the growing impact of deep learning and artificial intelligence in veterinary diagnostics, specifically for image-based disease detection. Many of the studies focus on the application of CNNs to various veterinary conditions, from ocular diseases like squamous cell carcinoma in cattle to broader health management applications in livestock. The research gaps identified here is, in many cases it fails to produce the accurate results and severity of the disease is not identified.

3 Proposed Deep Learning- Based Early Detection and Classification of OSCC

The proposed deep learning based early detection and classification of OSCC helps to young calf and care takers to identify the disease of the cattle easily and the system aims to provide the severity of the disease. The proposed system comprises of the 4 modules data collection, data preprocessing, OSCC detection and severity detection. The data is collected and processed for the preprocessing after the removal of noise the deep learning model is trained to classify the OSCC in young calf and cows and then severity of the disease is identified further and this information is intimated to the care taker of the cattle's as shown in figure 1.

3.1 Data Collection

Real-time cow eye images are captured using a mobile phone camera, while additional images are sourced from the internet. These collected images are then compiled to form a diverse cow eye dataset, which includes eye samples from multiple species of cows. The dataset serves as a valuable resource for various research and analysis purposes related to the characteristics of cattle eye.

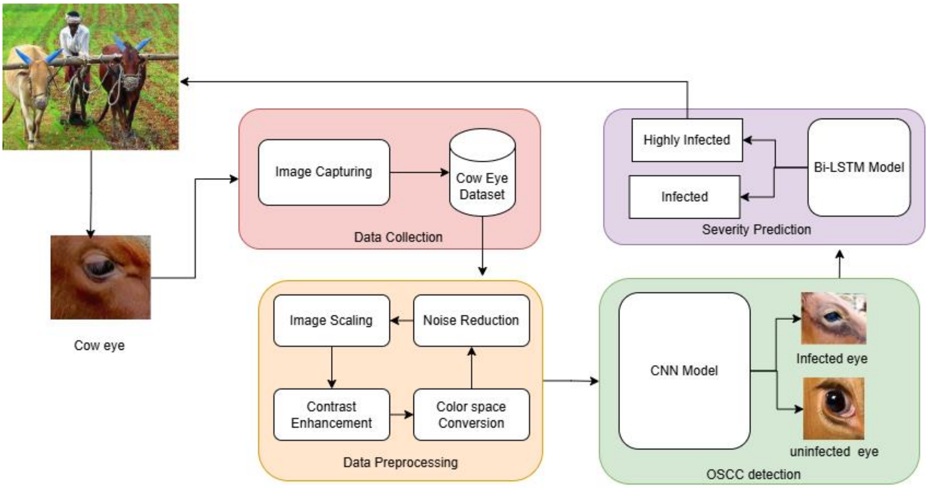

Fig 1. A Deep Learning Framework for Automated Detection and Severity Assessment of Ocular Squamous Cell Carcinoma in Cattle

3.2 Data Preprocessing

After the data is collected, image cleaning and filtering is performed, where noisy images and irrelevant images are removed from the dataset for the further processing and applying filters enhances the quality of the images and it helps to remove the artifact which interfere while analysis of an image and then the scaling is perfumed in which it helps to perform the resizing of the image where it rescale the image in standard size to ensure the uniformity. The contrast and color enhancement helps to identify the accurate portion of the cattle's eye in which it help to normalize the pixel value with respect to the standard range. Data augmentation is performed to increase the dataset diversity and it helps to prevent the over fitting where flipping rotating zooming are some of the transformations are performed with respect to the image.

3.3 OSCC detection

After the preprocessing, labeling is performed where the data are labelled into two classes where the data is imbalanced to overcome that, oversampling is performed. After sampling, the data is balanced and further the data is processed to the deep learning model where CNN model is used, an input layer accepts the cattle eye image which is typically a 3D tensor such as width, height and the channels. After data get processed from the input layer, the next layer is convolutional layer which extract the feature from the image where it applies filters to detect the accurate pattern which focuses on edges, spaces where ReLU is used to activation function for non-linearity. Pooling layer is used to reduce the overload and handles the over fitting problems by preserving the important features of the images and then the data is flattened into 1 dimensional vector where fully connected layer is used to provide an right decision based on the extracted features. A gradient descent based optimizer, an Adam is used to minimize the loss function. During training the model, weight is adjusted by using back propagation. After the model is trained it produce the output as infected or uninfected eye.

3.4 Severity Prediction

Once the disease is classified, then the threshold value is fixed and Bi-directional Long-short Term model is used to find the severity of the disease because it helps to capture long term dependencies and relations with data. The infected eyes are detected and processed for the severity prediction where image segmentation is performed to capture the relevant features and it convert the image into sequential feature vector for temporal analysis. The threshold value is fixed in between to ‘0’ and ‘1’ when the extracted feature cross the limit with respect to 0.5 then the severity is high and range with less than 0.5 then severity is low. Bi-lstm model is trained with the data where an input layer captures the temporal data and then Bi-LSTM layer process the features in both forward and backward direction in which it captures the past and future context. The dense layer aggregates the feature extracted from the bi-lstm layers. The output layer fetches the input from the dense layer where the output depends on the severity classification such high low and moderate

4 Implementation and Result Analysis

The real time data is collected where 10,234 images of the different cow eyes in the different regions is captured in which 4112 images are captured using the camera and remaining images are collected from the online source and synthetic dataset is formed and it is shown in the figure 2. The captured images are labeled into two categories as class 1 and class2.

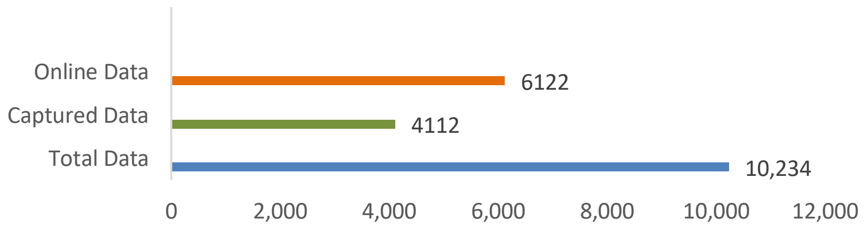

Fig 2. OSCC Data Collection

The collected synthetic dataset is further proceed to the preprocessing where noise removal, image filtering, quality enhancement and scaling are performed and unwanted data are removed where the 4,326 images are removed from the 10,234 eye images as shown in figure 3.

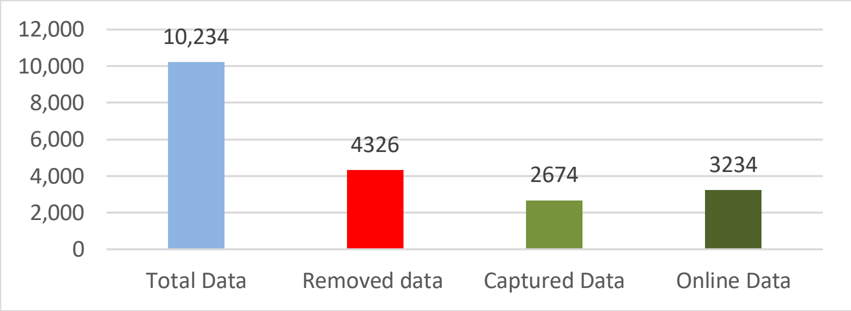

Fig 3. OSCC Data Collection after Pre-processing

Due to the data imbalancement the oversampling technique is performed to balance the data as shown in the figure 4. Then it proceed to model training in which CNN, DNN and ResNet50 models are trained

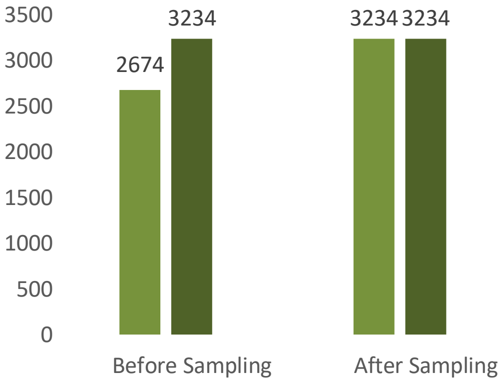

Fig 4. OSCC Data Sampling

CNN model provides the better performance when compared to the other models where the 15 layers CNN model is implemented using the google colab platform where tensorflow framework and keras library are used with graphical processing unit where the model is trained with 10 epochs and it took approximately about 1hrs 23 minutes to complete the training process. The model is executed multiple time to find the idle hyper parameter for the model. The three models are considered for training the data, CNN, DNN and ResNet50 is used in which the CNN produces the accuracy of 93% whereas DNN produces 82% and ResNet produces 85% accuracy mean while CNN produces the less loss with 0.9% whereas as the other model produces the more amount of loss. The convolution model starts with the input layer where the preprocessed data is processed further and the data is forwarded to the convolution layer with 8 layers where as in 1st two layers 32 filters are used with the 3*3 kernel size and 3rd and 4th layer another 64 filters are used with 3*3 the same way is followed for the other 4 layer for 5th and 6th layer 128 filters are chosen and 7th and 8th layer 256 filters are chosen.

The ReLu activation function is used with all the eight layers of convolution network. First layer in the network forms a set of one max pooling layer with batch normalization and it continue for other 6 layers where as the 8 layer produce the average of all max pooling layer as an output and it is taken as an input for dense layer with sigmoidal activation function. The data is flattened into 1 dimensional vector to provide a right decision where adam optimizer is used to reduce the loss function. Accuracy of CNN increases gradually and reaches 93% where as in DNN and ResNet50 produce a less accuracy as shown in figure 5, same as in performance of loss CNN leads to the less loss when compare to the other two models as shown in the figure 6.

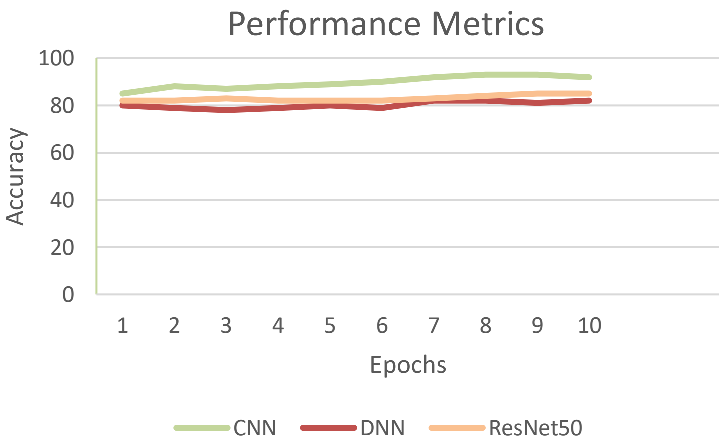

Fig 5 Comparison of Accuracy of DL Model for OSCC disease detection

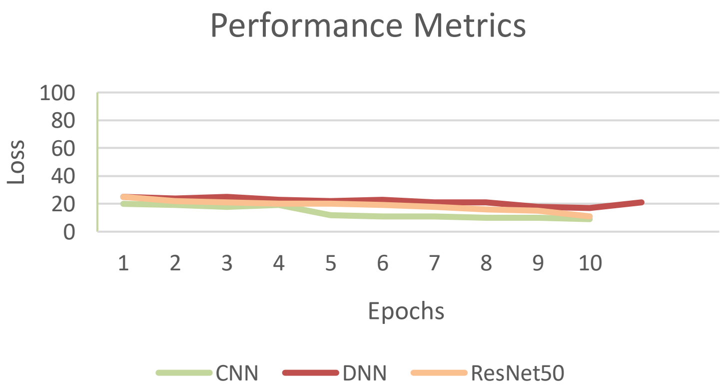

Fig 6 Comparison of Loss of DL Model for OSCC disease detection

Bi-directional Long- short Term model is used for finding the severity of the disease. Once the disease has been identified, the threshold value is fixed based on OSCC affected level where as 100% is taken as a high severity level. Input of the information is taken as the sequential feature vector for temporal analysis. Threshold value is fixed in between 0 and 1 when the suspected output of the image cross the limit 0.5 then it is considered to be high severity and if it is less than 0.5 then it is considered to be less severity. An input layer captures the temporal data and then embedding is performed where the given data is represented in the embedded form and the data is proceed to the bidirectional lstm layer helps to proceed the data in both the forward and backward direction and then max-pooling layer is used to capture the updated features of the image and then drop out and dense layer is performed.

Fig 7. Cow Disease Detectiion Application

The proposed system is designed as the website and final output of OSCC is shown in fig 7 where the non-infected eye with severity score is shown in fig 8 and non –infected eye with severity score shown in fig 9.

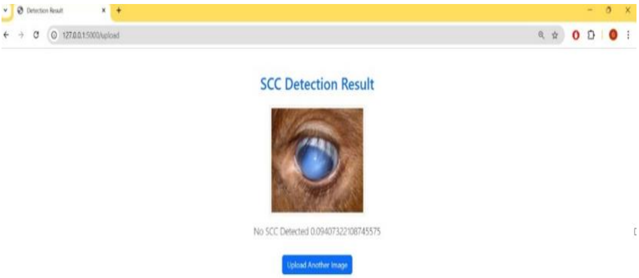

Fig 8. Non-infected eye with severity score

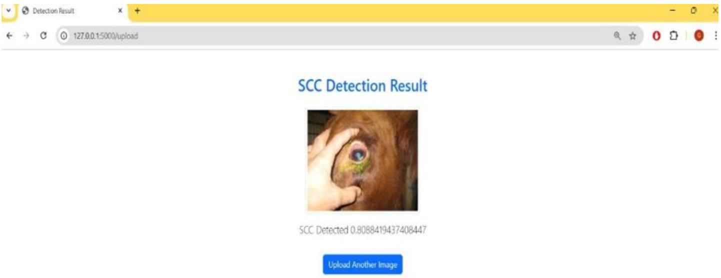

Fig 9. Infected eye with severity score

5 Conclusion and Future Work

The proposed system helps to identify the OSCC disease in earlier stage where it is developed to save the life of the cattle and unaware farmers. The proposed system is used to capture the eye of the cattle and other processing steps are performed to reduce the noise. The deep learning model such as Convolution Neural Network is used to identify the whether the eye is infected or not and Bidirectional Long Short Term Memory is used to identify the severity of the disease. The identification disease using naked eye is difficult but our proposed developed website helps the farmer to identify the disease of the cattle. In future, some feature can be added or by integrating deep learning model to produce a better accuracy than our model. The mobile application can be developed for the user friendly to detect the information is less time duration.

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