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ADVANCING LYME DISEASE PREVENTION THROUGH COMPUTER VISION: A ROBUST APPROACH FOR TICK IDENTIFICATION

Mr. P. Suresh[1], Ch. Lahari Priyanka[2], K. Murali Krishna[3], P.Kamal Srinivas[4], Y. Pavan Kumar[5]

[1]M. Tech, Assistant professor, Department of Electronics and Communication Engineering, Usharama College of Engineering and Technology, Andhra Pradesh, India
[2] B.Tech, Student, Department of Electronics and Communication Engineering, Usharama College of Engineering and Technology, Andhra Pradesh, India
[3] B.Tech, Student, Department of Electronics and Communication Engineering, Usharama College of Engineering and Technology, Andhra Pradesh, India
[4] B.Tech, Student, Department of Electronics and Communication Engineering, Usharama College of Engineering and Technology, Andhra Pradesh, India
[5] B.Tech, Student, Department of Electronics and Communication Engineering, Usharama College of Engineering and Technology, Andhra Pradesh, India

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ABSTRACT

Lyme is a disease that is caused by Borrelia burgdorferi, a bacterium that is spread by ticks. The prevalence of Lyme disease has made it a major public health problem. Immediate identification of the bacteria-carrying parasites is important in preventing the epidemic. This research suggests an alternative approach which uses computer vision to identify Lyme diseases related to ticks. A dataset containing images of ticks was used to create and train a Convolutional Neural Network (CNN) model. Preprocessing and augmentation were done on the dataset with split data into training and testing sets prior to boosting model generalization. The architecture of the CNN consists of convolutional, batch normalization and pooling layersfollowed by fully connected layers for classification. The Adam optimizer trains the model with a piecewise learning rate schedule. Test set evaluation shows promising results with high accuracy in categorizing tick pictures. Furthermore, this study calculates precision, recall and F1 score metrics which indicates strong performance from this model. A confusion matrix as well as visualization is also used to prove that model can distinguish between different tick classes. This computer vision approach provides a powerful tool for automatic tick recognition thus aiding in early detection as well as prevention of Lyme disease

KEYWORDS; *Image analysis, deep learning, tick identification, epidemiological surveillance, disease management, public health interventions, artificial intelligence, zoonotic diseases, tick-borne pathogens, predictive modeling.*

I.INTRODUCTION

Lyme disease, a tick-borne disease caused by the bacteria Borrelia burgdorferi, is a serious public health problem worldwide. Lyme disease can lead to serious health complications if not diagnosed and treated promptly. Early detection and identification of ticks carrying the bacteria that cause Lyme disease is critical for effective disease management and prevention. Traditional tick identification methods often rely on manual inspection by trained personnel, which can be time-consuming and labor-intensive. In recent years, advances in computer vision and machine learning techniques have opened up new possibilities for automatic tick identification.

Lyme disease usually begins with flu-like symptoms such as arthralgia, chills, fever, myalgia, and neck stiffness, with an erythema migrans rash appearing 2 to 30 days after a tick bite. Blackleg infection [5]-[7] . Antibiotic treatment usually eliminates B. burgdorferi infection; However, if left untreated, the infection can progress to disseminated disease

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with increased risk of morbidity, long-term sequelae, and post-treatment Lyme disease syndrome [6], [8]–[11]. Lyme disease can be prevented if antibiotic prophylaxis is given to the patient within 72 hours of the tick bite [11]. Understand where blacklegs and B. ticks are. Burgdorferi is critical in informing healthcare providers and the public about the risks of Lyme disease. Across North America, blacklegged tick monitoring is patchy (using various passive and active tools) or sometimes non-existent. In passive surveillance, ticks are submitted by healthcare providers or the public for identification and/or detection of B. burgdorferi [12]. . Active surveillance includes removing ticks from the environment or catching live animals. Active and passive surveillance are intended to monitor tick populations and are not designed for clinical use; Therefore, additional resources are required to assist the doctor in treating Lyme disease . In addition, these monitoring techniques are time-consuming, logistically demanding, and expensive to operate and maintain. In the clinical setting, healthcare providers need a faster response to determine whether a patient's tick is a blacklegged tick or another tick pest species. Healthcare providers and patients would benefit from a more rapid assessment of the affected tick species, as this could help decide whether to monitor a patient's symptoms or administer antibiotic prophylaxis.

This study aims to explore a computer vision-based approach for the identification of ticks related to Lyme disease. By training a CNN model on a dataset of tick images, this approach seeks to automate the process of tick detection and classification, thereby facilitating early intervention and disease prevention. The proposed methodology involves data preprocessing, model architecture design, training, and evaluation, with the ultimate goal of developing a reliable tool for tick identification in support of public health efforts against Lyme disease. The subsequent sections of this paper will delve into the methodology, results, and implications of employing a computer vision approach to tick identification, highlighting the potential benefits and challenges associated with this innovative approach.

II.METHODOLOY

Background

Automating the monitoring and identification of tick species using computer vision models could potentially be improved by advances in deep neural networks [17]. Convolutional Neural Network (CNN) is a class of deep neural networks most commonly used for computer vision tasks. However, training CNN models from scratch is not without complications and requires the collection and annotation of large datasets, which limits their use in healthcare [18]. A popular approach forto address this shortcoming is to exploit the “portability” of the knowledge embedded in pre-trained CNNs and transfer this knowledge from a known source task to a new target task [19]-[21]. The most widely used approach to knowledge transfer is transfer learning, where a deep source neural network is first trained on a large dataset such as ImageNet [22] (this is called pre- training) and then the weights are used. learned (knowledge) from networks. as an initialization to train a target deep neural networkon a smaller dataset such as medical images (this is called fine-tuning) [23], [24]. Fine-tuning requires minimal changes as some of the network parameters remain frozen during training [24], [25].

Transfer learning has been successfully applied to various computer vision tasks such as: B. Object classification and feature generation, both in the generic and medical areas [26]–[28]. However, depending on the problem, transfer learning may not be the best approach and may not provide any benefit, especially when the source and target domains are semantically and substantially different [17]. An alternative to learning transfer for heterogeneous areas is another knowledge transfer technique called a teacher-student learning framework. Knowledge transfer in teacher-student learning occurs between two different networks, namely a teacher network and a student network, where the student network is trained to mimic the results of a larger teacher network. and powerful or a set of teacher networks [19], [20]. One of the most popular training frameworks among teachers and students is that of Zagoruyko et al. proposed attention transfer. [29]. In this method, the teacher's feature maps guide the student to learn data patterns. With this approach, using the attention maps of a teacher network, the student network is trained to mimic the exact behavior of the teacher network by attempting to reproduce its output in a layer that receives the teacher'sattention.

In this work, we build our computer vision pipeline by using various knowledge transfer approaches (e.g., attention transfer) [29], [30] since our tick dataset is small (several thousand images). Additionally, our tick dataset contained several noisy and blurry images due to the presence of very small nymphal ticks. Therefore, in addition to attention transfer, we used Label Smoothing Regularization (LSR) [21] as a regularizer to improve the robustness and generalization of CNN models. LSRconverts one-hot coded labels (hard labels) into soft labels with an even distribution mix. In addition to model improvement, both attention transfer and LSR provide benefits for model

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compression [20], [31] and enable deployment of CNN models on mobile phones or website applications.

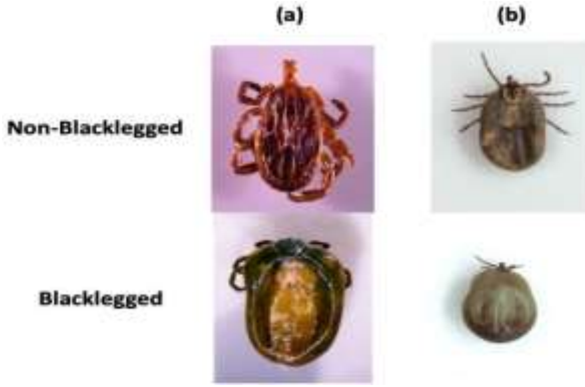

Figure 1.1 (a) High-resolution microscopic images,
(b) cell phone images of fed ticks, and (c) cell phone images of unfed ticks. Completely or lightly engorged ticks can triple in volume when filled with blood.

The proposed model aims to identify ticks related to Lyme disease using a computer vision approach.
1.Data Loading and Preprocessing :
The model starts by loading a dataset of tick images. These images are organized into folders based on their respective classes (e.g., tick carrying Lyme disease, non-Lyme disease tick). The `imageDatastore` function is used to load the dataset, specifying options such as including subfolders and labeling based on folder names. The dataset is then split into training and testing sets using an 80-20 split ratio.

2.Model Architecture :The model architecture is defined using a Convolutional Neural Network (CNN).The input image size is set to 256x256 pixels with three channels (RGB).MThe CNN architecture consists of several layers:
Image Input Layer Accepts input images and performs z-score normalization. Convolutional layers extract features from input images through convolution operations. Each convolutional layer is followed by batch normalization and a Rectified Linear Unit (ReLU) activation function. Max- pooling layers downsample the feature maps to reduce spatial dimensions while preserving important features. And Fully Connected Layers perform classification based on the extracted features. The number of neurons in the output layer corresponds to the number of classes. Softmax layer converts the output scores into probabilities, indicating the likelihood of each class.

Classification Layer: The final layer assigns the input image to one of the classes based on the highest probability.

Model Training: The model is trained using the training dataset and the specified training options. The Adam optimizer is used for optimization. Training progresses through epochs, with mini-batches of data shuffled at each epoch. Learning rate scheduling with a piecewise drop factor and drop period helps in effective optimization.

4.Model Evaluation & Model Deployment
Once trained, the model is evaluated using the testing dataset to assess its performance. Classification accuracy, confusion matrix, precision, recall, and F1 score are calculated to evaluate the model's effectiveness in identifying ticks related to Lyme disease. After evaluation, the model can be deployed to classify new images of ticks. Users can provide input images, and the model will classify them as either carrying Lyme disease or not.

Training Models and Frame
In this work, automated blacklegged tick identification is presented as a binary classification task in which a CNN model is trained to predict class labels for given tick images using the following training strategies:

1)Training the CNN models from scratch with random initialization, with all layers open for optimization during training. In this context, two CNN architectures were used, including Inception-Resnet [33] and a lighter CNN model developed for this study. The lightest CNN model consisted of 7 convolutional layers followed by batch or dropout normalization. Additionally, average pooling layers were used

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to reduce the number of parameters. In total, the network had 13 layers with 5,350,633,trainable parameters out of 5,352,041 parameters (see Appendix A for more details of the network).

2)Transfer the learning of a pre-trained Inception Resnet CNN network to ImageNet. Two sets of experiments were conducted in this environment, including opening all CNN layers for optimization and unfreezing only the last five layers during training.

3)Transferring the attention of an Inception Resnet teacher [33] previously trained on ImageNet. In this scenario, the knowledge is transferred to the student network, which was the lightest CNN model with and without LSR. Attention transfer: Following the work of Zagoruyko et al. [29], we construct an activation-based attention transfer to transfer knowledge from the last layer of the teacher network (Inception-Resnet) to the layer before the last layer of the student network (Lighter CNN), as shown in Fig. 2. Theknowledge transferred to our environment is a spatial attention map created by taking the sum of the absolute values of the 3D tensor of a layer A ∈ R C×H×W over the channel dimension:

To calculate the attention transfer loss between the teacher's and student's spatial attention maps of the same resolution (with the same height, H, and width, W), we use \(l_2 \) normalization. Let's denote the spatial attention map of the teacher network as \(Q_T \) and the spatial attention map of the student network as \(Q_S \). Both \(Q_T \) and \(Q_S\) are 2D tensors with dimensions \(H \times W \).

The attention transfer loss is calculated as follows:

$$\|Q_T\|_2 = \sqrt{\sum_{i=1}^{H}\sum_{j=1}^{W}(Q_T(i,j))^2}$$

$$\|Q_S\|_2 = \sqrt{\sum_{i=1}^{H}\sum_{j=1}^{W}(Q_S(i,j))^2}$$

2. Next, we normalize the attention maps by dividingeach element by its corresponding norm:
This attention transfer loss quantifies the dissimilaritybetween the spatial attention maps of the teacher and student networks, providing a measure of how well the student network is learning to attend to relevant regions compared to the teacher network. Minimizing this loss encourages the student network to mimic the attention patterns of the teacher network, facilitating knowledge transfer in the context of attention mechanisms.

Overall, the proposed model offers a data-driven approach to automate the identification of ticks associatedwith Lyme disease, providing a valuable tool for disease surveillance and prevention efforts.

III.RESULTS AND DISCUSSION

This section presents the classification results obtained byapplying various CNN models to the tick dataset. For model development and evaluation, our data set was split into a train/test split with a ratio of 11/1 with no overlap. Therefore, 12,554 images (41% with black legs) for the training set and 1034 (41% with black legs) for the testing set were used to validate the performance of the developed model.

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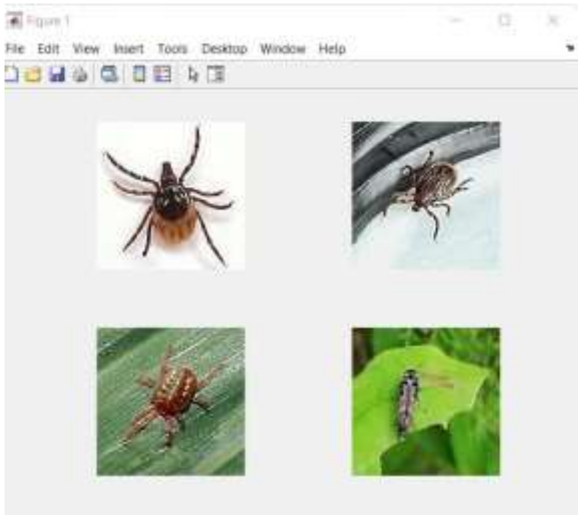

The training data was enhanced with 0◦ -360◦random rotation, horizontal rotation, vertical rotation and a 0.5x to 2x zoom range. Adam was used to optimize the loss function inall experiments. Cross-validation (k = 3-fold) was used tooptimize the hyper parameters. The input image sizes for the lighter CNN model and the Convnet network were 300 × 300 and 299 × 299, respectively. The lighter CNN model was trained for a maximum of 256 epochs with an initial learning rate of 10-3 and a batch size of 64. For the attention transfer approach, the classification loss was the combination of LAT and binary cross-entropy loss. For the attention transfer + LSRapproach, the loss parameters (Equation 3), including β1, β2, and T, were set to 1, 2, and 5, respectively. Table 1 shows the results of our first experiment comparing the training performance of the lighter and standard Inception Resnet CNNmodels [33].

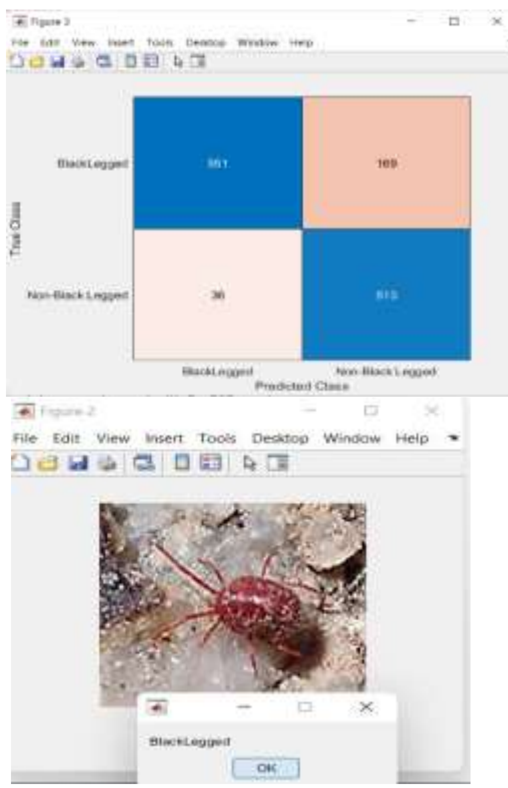

Fig Confusion Matrix & Predicted result

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The performance of using different strategies, including network size and initialization, to train CNN classifiers to distinguish between the two common tick species; Blacklegged ticks versus dog ticks. The best results in each column are in bold and the second best results are underlined. ROC-AUC is the area under the ROC curve and PR-AUC is the area under the precision recovery curve. Regardless of initialization, CNN models with a larger number of trainable parameters perform better on the tick dataset. The performance of the CNN classifier is very poor when the initial layers are fixed during training. *Only the last 5 layers Covnet were optimized, while the rest of the CNN in the table was trained from scratch without frozen layers.

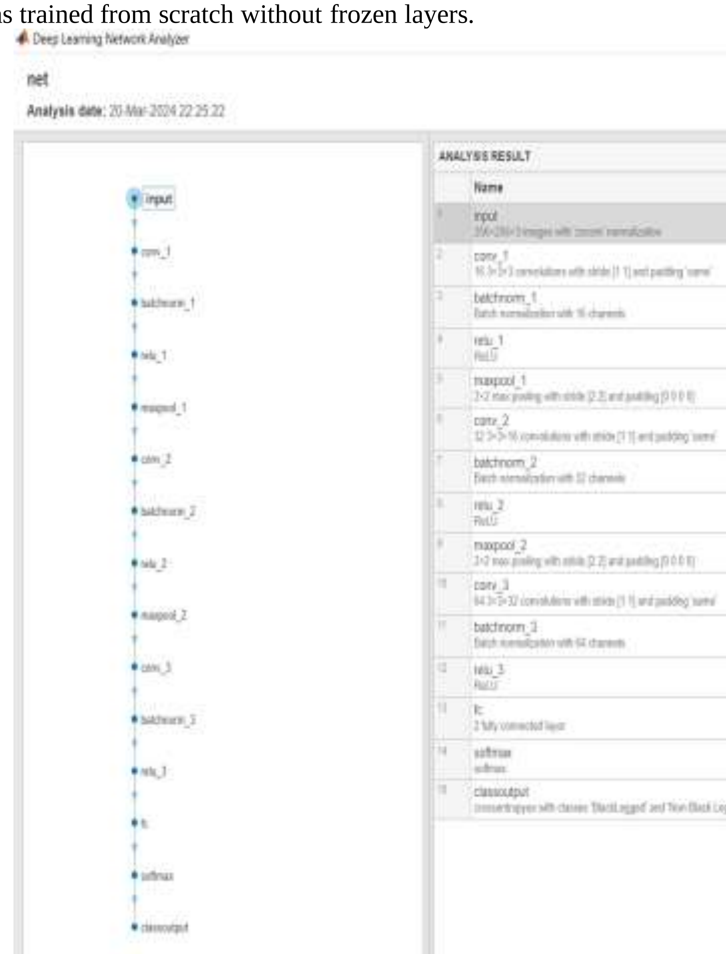

Fig CNN Architecture

We provide preliminary evidence that advanced deep learning technologies hold promise for improving blacklegged tick monitoring. Additionally, there is an opportunity to further refine the technology to classify other tick species. However, further study is needed on how to integrate these

technologies into an affordable, responsive, targeted and user- friendly tool for end users. Our current and future work will inform those interested in further developing and deploying deep learningmodels in the area of infectious disease surveillance and diagnosis.

IV.CONCLUSION

Based on the findings derived from this study, the following conclusions were drawn:

1. The proposed computer vision-based approach to identifying ticks associated with Lyme disease provides a robust solution to an urgent public health problem.

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2. Using Convolutional Neural Networks (CNN) and a carefully selected dataset, the model demonstrates high accuracy in distinguishing between tick classes.
3. The effectiveness of the approach is carefully validated through careful data preprocessing, comprehensive model training, and rigorous evaluation against a dedicated test set.
4. Visualization ofresults, including confusion matrices and accuracy measures, helps further validate the reliability and performance of the model.
5. This study highlights the enormous potential of computer vision techniques to address complex public health challenges such as Lyme disease.
6. By automating the lengthy and error-prone process of tick detection, the proposed model provides a valuable tool for early detection and targeted prevention measures

V. RECOMMENDATIONS

Based on the findings and conclusions, the following recommendations are offered.

1. Quickly and accurately identifyingticks in the images could significantly help health authorities and researchers monitor tick populations, identify high- risk areas, and implement rapid intervention strategies to reduce communicable diseases.
2. Looking forward, there are several directions for future research and development that will improve the effectiveness and relevance of the proposed model.
3. Expanding and diversifying the dataset, exploring advanced transfer learning techniques, integrating attention mechanisms into the CNN architecture, and exploring real-time-based implementation methods in field conditions are promising directions.
4. In addition, expanding the model to classify ticks into more classes and improving its interpretability and explainability can increase its utility and increase stakeholder confidence.
5. Continuous innovation and collaboration in this area has the potential to revolutionize public health surveillance and make a significant contribution to the prevention and control of tick-borne diseases.

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CONFLICT OF INTEREST

The authors have declared that there is no conflict of interest.

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