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Artificial intelligence-assisted ultrasonographic evaluation of the superficial inguinal lymph node for the diagnosis of mastitis in dairy cows

Evaluación ultrasonográfica asistida por inteligencia artificial del nódulo linfático inguinal superficial para el diagnóstico de mastitis en vacas lecheras.

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ABSTRACT

Mastitis is one of the most significant infectious diseases affecting dairy cattle. It has a drastic impact on the animals welfare and poses serious economic losses to dairy production. In addition to examining the milk, evaluating the mammary tissue, especially the superficial inguinal (supramammary) lymph nodes, are essential for diagnosis and prognosis. This study aims to assess the effectiveness of artificial intelligence -based deep learning models in detecting mastitis from ultrasonography images of superficial inguinal lymph nodes. The study was conducted on 252 Brown Swiss cows aged 3–6 years, which were classified into three groups according to the California Mastitis Test and clinical examination: clinical mastitis (n = 84), subclinical mastitis (n = 84) and a control group (n = 84). Six pre-trained deep learning architectures were used to process B-mode ultrasonographic images: MobileNetV3, EfficientNetV2B3, Xception, InceptionV3, NasNet, InceptionResNetV2 and ConvNeXtSmall. All models performed satisfactorily, with EfficientNetV2B3 achieving the highest accuracy (96.87 %), precision (97.53 %) and F1 score (96.79 %), with a area under the curve of (100 %). These results suggest that integrating ultrasonographic and echotextural data with an AI-based model could be a valuable resource for the early detection and accurate diagnosis of mastitis, in line with the goals of precision livestock farming.

Key words: Mastitis, artificial intelligence, lymph node, cattle.

RESUMEN

La mastitis es una de las enfermedades infecciosas más importantes en el ganado lechero, ya que afecta negativamente al bienestar animal y provoca pérdidas económicas significativas en la industria láctea. Además del análisis de la leche, la evaluación del tejido mamario y de las estructuras linfáticas asociadas, particularmente los nodes linfáticos superficial inguinal, desempeñan un papel relevante en el diagnóstico y el pronóstico. El presente estudio tuvo como objetivo investigar el potencial de modelos de aprendizaje profundo basados en inteligencia artificial para la detección de mastitis mediante el uso de imágenes ultrasonográficas de ganglios linfáticos supramamarios. Se incluyeron un total de 252 vacas Brown Swiss de entre 3 y 6 años de edad, clasificadas en tres grupos según los resultados de la Prueba de Mastitis de California y los hallazgos del examen clínico: mastitis clínica (n = 84), mastitis subclínica (n = 84) y grupo control (n=84). Las imágenes ultrasonográficas en modo B fueron analizadas utilizando seis arquitecturas de aprendizaje profundo preentrenadas, incluyendo MobileNetV3, EfficientNetV2B3, Xception, InceptionV3, NasNet, InceptionResNetV2 y ConvNeXtSmall. Se aplicaron técnicas de aumento de datos y el rendimiento de los modelos se evaluó en los conjuntos de entrenamiento y validación mediante métricas de exactitud, precisión, sensibilidad, F1-score, pérdida y área bajo la curva. Todos los modelos demostraron un rendimiento satisfactorio, destacándose EfficientNetV2B3 con la mayor exactitud (96,87 %), precisión (97,53 %), F1-score (96,79 %) y área bajo la curva (100 %). Estos resultados indican que la integración de parámetros ultrasonográficos y ecotexturales con modelos basados en inteligencia artificial puede mejorar la detección temprana y precisa de la mastitis y contribuir al desarrollo de prácticas de ganadería de precisión.

Palabras clave: Mastitis, inteligencia artificial, nodes linfático, bovino lechero.

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INTRODUCTION

Maintaining udder health is important for animal welfare and economic efficiency in dairy cattle (*Bos taurus*). Superficial inguinal lymph nodes are part of the mammary-associated lymphatic system and are involved in critical pathological processes, especially mastitis. In cattle, the mammary quarters are fully independent, and the lymphatic drainage of each pair drains to the corresponding superficial inguinal lymph nodes on that side. Typically, one or two superficial inguinal lymph nodes are present on each side, only superficially attached to the udder [1].

These nodes are thin or oval-shaped echogenic capsules with hyperechoic hilums and hypoechogenic cortices [1, 2]. However, in certain situations, such as mastitis, lymphocyte proliferation and activation occur within these nodes, resulting in size and ultrasonographic changes [3]. These structural changes can be evaluated using a noninvasive, reliable, and safe method, such as ultrasonography (USG). Superficial inguinal lymph nodes may become highly enlarged, even in subclinical mastitis [2, 4].

In recent years, artificial intelligence (AI)-based approaches have become increasingly important in veterinary medicine. Algorithms for image processing and deep learning models, which are trained using data obtained from non-invasive methods such as USG and thermography, have helped with the early diagnosis of mastitis and lymph node changes [5, 6, 7, 8].

For example, AI-assisted systems can quickly and objectively assess the size, shape, and vascularization of superficial inguinal lymph nodes, which is faster than the time-consuming subjective clinical examination. Furthermore, the developed machine learning models are capable of predicting herd-level disease status using either milk yield data or lymph node characteristics as standalone inputs, thereby facilitating evidence-based herd health management. [5, 6, 7].

Anatomical, histological, immunological, ultrasonographic, morphometrical, and echotextural studies emphasize the necessity of these processes for the early detection of mastitis and systemic diseases in clinical practice. A key highlight of these processes is the adoption of AI, which supplements traditional diagnostic approaches and signals a paradigm shift in clinical practice, introducing more accurate, faster, and predictive methods in the near future.

MATERIALS AND METHODS

Experimental units

This study was conducted on 252 clinically healthy Brown Swiss cows (except for mastitis), obtained from the Agriculture and Livestock Research Center at Fırat University in Elazığ province. The cows were between three and six years old and had a body condition score between 2.75 and 3.50. The cows were examined using a previously described unequally spaced design. Throughout the experimental period, the cows were managed and fed a mixture of grass, wheat straw (*Triticum aestivum*), and cattle feed under normal conditions.

Ethical approval for this experiment was granted by the Fırat University Local Ethics Committee for Animal Experiments (FU/HADYEK-2021-28597).

Groups

The animals were grouped according to their California Mastitis Test (CMT) score [9] and clinical examination findings into three groups:

1. **Clinical mastitis group (n = 84):** Udder quarters displaying clinical signs such as fever, skin inflammation and clots.
2. **Subclinical mastitis group (n = 84):** Animals that showed a positive reaction in at least one udder quarter on the CMT.
3. **Control group (n = 84):** Animals with a negative CMT result in all udder quarters.

After CMT scoring, images of the superficial inguinal lymph node of these subjects were taken and stored using USG (IBEX Pro, USA). All procedures were performed by a single operator to ensure standardisation.

Ultrasonographic imaging of superficial inguinal lymph nodes

Superficial inguinal lymph nodes were imaged using an (IBEX Pro, USA) B-mode real-time USG device with a 5 MHz linear probe. The probe was held upright with ultrasound gel, and all measurements were taken by the same operator using the same device and settings (gain, MHz, etc.) (FIG. 1).

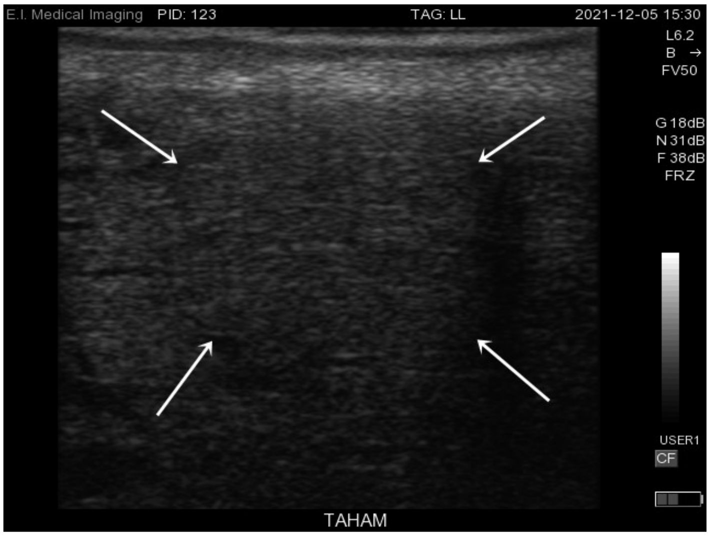

FIGURE 1. Superficial inguinal lymph node of a cow (indicated by the arrows) in a B-mode ultrasonographic image

Dataset

The dataset included the following classifications of superficial inguinal lymph nodes:

-Group 1: CMT-negative (control);

-Group 2: CMT-positive;

-Group 3: clinical mastitis.

The objective of this study was therefore to develop an image processing system that could classify superficial inguinal lymph node images as healthy or diseased, and to use this information alongside machine learning models to predict mastitis in cattle.

Model structure

This experiment is based on six pre-trained models. The base models chosen were MobileNetV3, EfficientNetV2B3, Xception, InceptionV3, NasNet, InceptionResNetV2 and ConvNeXtSmall. MobileNets are optimised for fast inference without losing much accuracy, and are thus specifically designed for mobile devices [10]. EfficientNets achieve even greater efficiency than MobileNets by scaling network depth, width, and input resolution simultaneously [11, 12]. Xception stands for 'Extreme Inception', which takes the Inception architecture to the extreme [13]. Inception models use a unique layer structure where the employed blocks are designed to process the layer in parallel, followed by concatenation [14]. NasNet: (Neural Architecture Search Network), the topology of a neural network can be systematically explored to discover the best architecture for a given task. Candidates are first evaluated on a small subset of data, and then the model is optimised [15].

InceptionResNet models combine the advantages of the Inception architecture and residual mappings from ResNet and often outperform models based on either modality alone [16]. ConvNeXt overview The ConvNeXt models were designed to upgrade convolutional neural networks (CNNs) following the successful introduction of vision transformers. ConvNeXt architectures (next-generation CNNs) offer greater accuracy, albeit at the expense of efficiency, and are available in multiple sizes. ConvNeXtSmall was selected for this experiment due to its balance of accuracy and computational efficiency [17].

These experiments were performed separately using different pretrained model setups. In addition to acquiring and implementing pretrained models, some extra steps were taken at various stages. This dataset comprises 252 images, divided into three splits: 70 % for training the model; 20 % for validating the model during training; and the remaining 10% for estimating the final performance or as a test set. A data augmentation layer was run over the dataset to generate synthetic data. Using image data augmentation techniques such as flipping, rotation, cropping and scaling, the original set of 252 images was expanded tenfold, thus enhancing the diversity of the training data.

The images in the dataset were distorted into one-dimensional arrays of RGB pixel values, each of which took a value from 0 to 255. These values were normalised to fit the [0, 1] or [-1, 1] range, depending on the pretrained model's requirements for faster, more efficient computation. Then, a preprocessing layer was added to ensure the correct shape of the model input. In this study, pretrained base models were used with a TensorFlow implementation of the program based on transfer learning to leverage prior knowledge and improve performance.

This study deploys a global average pooling layer to compute the mean of each feature map. This preserves essential features while reducing dimensions. This layer was set up in parallel with a prediction layer to produce the final outputs directly. Next, a softmax activation function was applied to determine the probability that each input image belongs to a particular class. After 100 epochs, both the training and validation sets have been processed. After each epoch, the loss and metric values were recorded to generate a training history for post-training analysis.

After training was complete, learning curves were plotted for each epoch, showing the metric and loss values. These graphs helped to visually understand the CNN model, its learning trend by epoch, and areas where the model could improve. The final step was to show the model's complete predictions together with the input images. These predictions were then visualized with an interface that allowed for direct comparison between the model's numerical outputs and the images from which they were derived. This provided a more nuanced understanding of the model's performance.

RESULTS AND DISCUSSION

All experiments were carried out in the Google Colab cloud environment. They were carried out using the Google Colab TPAV2 processor, which is a specialised unit designed to accelerate two-dimensional matrix computations, the core of neural network processing.

Finally, the layer responsible for making predictions for classification used a softmax activation function to calculate one-dimensional vectors of length equal to the number of classes. Each element of the vector corresponds to the probability of the input belonging to a certain class, with the sum of all elements equalling 1. The predicted class is taken to be the one with the highest probability value in the vector. Therefore, two-dimensional input images were transformed into a numerical value representing the specific class label.

Three classification models were evaluated in total. Six evaluation metrics — accuracy, cross-entropy loss, precision, F1-score, recall and ROC area under the curve (AUC) — were used to determine the most suitable model. The metrics were thoroughly evaluated for each model.

- **Accuracy:** The number of correct predictions made by the model divided by the total number of predictions.
- **Precision=** [true positives (TP) + false positives (FP)] This indicates the proportion of cases that model classified as positive that are actually positive.
- **Recall:** The proportion of correctly identified TP to the total number of actual positives [(TP + false negatives (FN)].
- **The F1-score** is the harmonic mean of precision and recall. If you need to balance precision and recall, this metric can help.
- **ROC AUC:** This is the most prominent metric and estimates how well a class can separate positives from negatives. The ROC curve shows the true positive rate versus the false positive rate, and the ROC AUC measures the entire two-dimensional area.

A model trained in epochs (defined as the number of runs, along with the metrics generated at every epoch) allows you to visualize the learning process. TABLE I and FIGS. 2 and 3 show accuracy trends that are consistent with the training and validation datasets. The maximum accuracy values were obtained by EfficientNetV2B3 (96.87 %) and ConvNeXtSmall

(96.66 %) (FIG. 2). The mean classification loss value was lowest for EfficientNetV2B3 and ConvNeXtSmall (both 0.05) (FIG. 3). All measurement methods created from the test dataset were able to conduct performance evaluations, yielding objective results. As shown in TABLE I, this model (EfficientNetV2B3) produced the highest performance metrics on the test set, confirming 96.87 % accuracy, 97.53 % precision, 96.79 % F1-score, and a remarkable ROC AUC of 100 %. For recall, ConvNeXtSmall produced the greatest value at 96.28 %. ConvNeXtSmall achieved an equal lowest loss value of 0.05 with EfficientNetV2B3.

Overall, the results show that EfficientNetV2B3 produced the best performance, confirming it as the best model in this study.

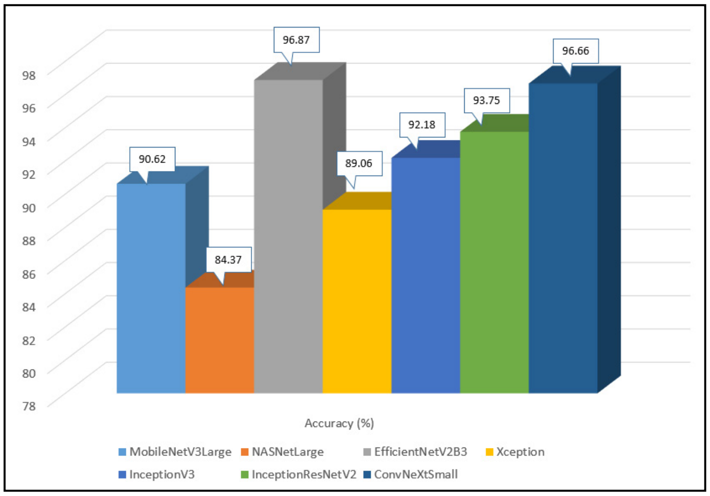

FIGURE 2. Alternative classification accuracy of deep learning models. This figure shows the classification accuracy of some deep-learning models: EfficientNetV2B3 (96.87 %), ConvNeXtSmall (96.66 %), InceptionResNetV2 (93.75 %), InceptionV3 (92.18 %), MobileNetV3Large (90.62 %), Xception (89.06 %) and NASNetLarge (84.37 %)

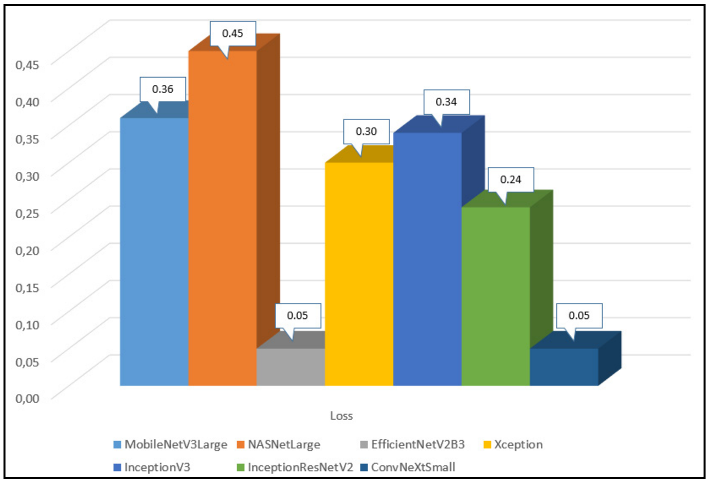

FIGURE 3. Comparative loss value of deep learning models. The figure shows the loss value for various deep learning architectures. NASNetLarge shows the highest loss value (0.45), followed by MobileNetV3Large (0.36), InceptionV3 (0.34), Xception (0.30) and InceptionResNetV2 (0.24)

Mastitis is one of the most important infectious diseases affecting dairy cattle, with considerable effects on animal welfare and the economic efficiency of dairy farming. In addition to milk analyses, mastitis diagnosis and prognosis can be informed by evaluating mammary tissue behaviour and its corresponding lymphatic system. Superficial inguinal lymph nodes are critical anatomical compartments that reflect local immunity to mastitis. Superficial inguinal lymph nodes are small and tend not to be easily palpated in the absence of mastitis, whereas they can be greatly enlarged as a result of lymphocyte proliferation and inflammatory cell infiltration during mastitis [18].

Ultrasonographic studies have shown that alterations in lymph node size and echogenicity are significantly correlated with the occurrence and severity of mastitis. For instance, study [2] found that the size of the superficial inguinal lymph nodes was significantly larger in cows with subclinical mastitis than in healthy animals. Similarly, [4] reported that, when analysed by colour Doppler USG, the lymph nodes of mastitic animals had higher vascular density, which corresponded with increasing CMT scores.

More recently, echotextural analysis has emerged as a new method of evaluating superficial inguinal lymph nodes. This method provides quantifiable indicators of tissue dispersion and inflammatory changes, as reflected by mean pixel intensity and pixel intensity standard deviation. Marked echotextural variations have been observed in superficial inguinal nodes affected by mastitis [19], suggesting that these non-invasive indices can be used as a clinical tool to distinguish between clinical and subclinical mastitis.

Thus, integration of echotextural analysis provides a much more objective and reproducible diagnostic approach than subjective interpretations of ultrasound imaging and CMT.

The gradual evolution of AI and deep learning techniques in Veterinary Medicine creates new opportunities for carrying out diagnostic workups, including assessing superficial inguinal lymph nodes. Image processing methods that use data acquired through non-invasive means, such as USG and thermography, can achieve a very high level of accuracy in diagnosing mastitis. [8], analysed ultrasonographic images of buffaloes (Bubalus bubalis) using a model based on EfficientNet-B3, achieving an accuracy of 75.93 % in mastitis detection. Similarly, subclinical mastitis was classified with 92.1 % accuracy using thermal imaging together with ResNet50 [7].

This study examined the classification performance of several deep learning architectures in terms of loss, accuracy, precision, recall, F1 score and ROC-AUC. The results revealed the strengths and weaknesses of each model. The EfficientNetV2B3 model achieved the best classification accuracy of 96.87 %, while other models (MobileNetV3L, InceptionV3, InceptionResNetV2

TABLE I
COMPARATIVE PERFORMANCE OF CLASSIFICATION MODELS

Base Model	Loss	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	ROC AUC (%)
MobileNetV3Large	0.36	90.62	94.04	84.13	88.81	97.24
NASNetLarge	0.45	84.37	88.19	77.79	82.67	95.83
EfficientNetV2B3	0.05	96.87	97.53	96.07	96.79	100.0
Xception	0.3	89.06	90.47	86.45	88.41	98.4
InceptionV3	0.34	92.18	93.25	84.41	88.61	97.17
InceptionResNetV2	0.24	93.75	95.23	90.76	92.94	99.22
ConvNeXtSmall	0.05	96.66	96.28	96.28	96.28	99.91

and ConvNeXtSmall) also performed well, achieving accuracies above 90 %. EfficientNetV2B3 and ConvNeXtSmall in particular achieved higher accuracy (96.87 % and 96.66 %, respectively) and lower loss values (0.05) than all the other architectures employed in this study. EfficientNetV2B3 achieved a perfect ROC AUC score of 100 %, indicating remarkably high performance in distinguishing between classes.

Previous sequential models, such as MobileNetV3Large, Xception and InceptionV3, achieved accuracies ranging from 89 % to 92 %. While these results remained within acceptable margins, there was a clear performance gap compared to modern architectures. For example, MobileNetV3Large achieved an accuracy of 90.62 %, but the recall rate was only 84.13 %, indicating insufficient sensitivity to certain classes. NASNetLarge had significant limitations as a result of a poor F1 score despite its complex architecture, achieving an accuracy of 84.37 % and an F1 score of 82.67 % (recall: 77.79 %).

By way of comparison, InceptionResNetV2 achieved a similar level of accuracy (93.75 %) and an F1-score of 92.94 %. Its good balance of precision and recall, along with an ROC AUC of 99.22 %, reinforces its position as one of the best candidates for real-world applications. Taken together, our results conclusively demonstrate that the more recent architectures (EfficientNetV2B3 and ConvNeXtSmall) offer definitive advantages in terms of both accuracy and generalisation ability. While older and more popular architectures still perform reasonably well for few-shot tasks based purely on benchmarks, they are limited, as all three measures show log-mean recall of less than 0.65 and F1-scores below the optimal level. Architectural improvements are crucial to advancing deep learning research, a fact that this study has helped to reiterate. Additionally, the results of this study validated the potential of AI as a trustworthy, clinical-friendly tool for early-stage mastitis diagnosis.

Although few studies have applied AI directly to superficial inguinal lymph nodes, combining ultrasonographic measurements and echotextural parameters of these nodes with AI algorithms may enable a more precise and efficient assessment of mastitis and other systemic infections. In particular, machine learning models that relate lymph node size, vascularisation and echotextural data to milk yield parameters are likely to become powerful tools for predicting mastitis and managing herd-level health.

CONCLUSION

This study explored the potential of using artificial intelligence-based inference approaches to detect mastitis. Traditional diagnostic techniques, such as milk analysis, clinical examination, and laboratory testing, are relatively costly and time-consuming. AI-assisted models, on the other hand, allow for the processing of large datasets in a relatively short period of time, increasing precision and optimizing clinical diagnostic decision-making.

Deep learning and machine learning algorithms were most effective in diagnosing early-stage mastitis, probably due to their ability to handle various input types, such as sensors, imaging modalities, and other clinical variables. Importantly, reducing false positives and negatives directly improves treatment outcomes by enabling veterinarians to make more reliable decisions.

In conclusion, these AI-based approaches serve as valuable assistants for mastitis diagnosis and can be incorporated into intelligent herd management systems for cattle. Widespread adoption of these technologies could represent a significant step toward improving animal welfare and advancing sustainable milk production. Moreover, the ultrasonographic image analysis and artificial intelligence methodologies described in this study may also have potential applications in the evaluation of other diseases affecting the superficial inguinal lymph nodes, such as bovine enzootic leukosis. Further studies are needed to compare different AI architectures in real-world settings, validate their applicability across different lymph node pathologies, and provide more tangible solutions for precision livestock management.

Ethical statement

All animal experiments were conducted in accordance with the approvals of Fırat University Local Ethics Committee for Animal Experiments (Approval no: FU-HADYEK-2021/28597).

Conflicts of interest

The authors have no conflicts of interest to declare in relation to the publication of this article.

Author Contributions

BFY: Conceptualization, Methodology, Visualization, Writing – Original Draft, Formal Analysis, Reviewing & Editing. MK: Methodology, Investigation, Formal Analysis Visualization. CK: Validation, Investigation, Supervision.

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BIBLIOGRAPHIC REFERENCES

[1] Bradley K, Bradley A, Barr F. Ultrasonographic appearance of the superficial supramammary lymph nodes in lactating dairy cattle. Vet. Rec. [Internet]. 2001; 148(16):497-501. doi: https://doi.org/d28mfx

[2] Khoramian B, Vajhi A, Ghasemzadeh-Nava H, Ahrari-Khafi MS, Bahonar A. Ultrasonography of the supramammary lymph nodes for diagnosis of bovine chronic subclinical mastitis. Iran. J. Vet. Res. [Internet]. 2015 [cited 20 Mar 2026]; 16(1):75-77. PMID: 27175155. Available in: https://goo.su/tZiG4

[3] Kehrli ME Jr, Harp JA. Immunity in the mammary gland. Vet. Clin. N. Am. Food Anim. Pract. [Internet]. 2001; 17(3):495-516. doi: https://doi.org/rfrr

[4] Risvanli A, Dogan H, Safak T, Kilic MA, Seker I. The relationship between mastitis and the B-mode, colour Doppler ultrasonography measurements of supramammary lymph nodes in cows. J. Dairy Res. [Internet]. 2019; 86(3):315-318. doi: https://doi.org/rfrs

[5] Themistokleous KS, Sakellariou N, Kiossis E. A deep learning algorithm predicts milk yield and production stage of dairy cows utilizing ultrasound echotexture analysis of the mammary gland. Comput. Electron. Agric. [Internet]. 2022; 198:106992. doi: https://doi.org/rfrt

[6] Wang Y, Kang X, He Z, Feng Y, Liu G. Accurate detection of dairy cow mastitis with deep learning technology: A new and comprehensive detection method based on infrared thermal images. Animals. [internet]. 2022; 16(10):100646. doi: https://doi.org/g9wnt2

[7] Silva RABd, Pandorfi H, Cordeiro FR, Soares RGF, Medeiros VWCd, Almeida GLPd, Barbosa-Filho JAD, Marinho GTB, Silva MV. A new way to identify mastitis in cows using artificial intelligence. AgriEngineering. [Internet]. 2024; 6(4):4220-4232. doi: https://doi.org/rfrv

[8] Zhang X, Li Y, Zhang Y, Yao Z, Zou W, Nie P, Yang L. A new method to detect buffalo mastitis using udder ultrasonography based on deep learning network. Animals. [Internet]. 2024; 14(5):707. doi: https://doi.org/rfrw

[9] Vural R, Ergün Y, Özenç E. Büyük ruminantlarda mastitis. In: Kaymaz M, Fındık M, Rişvanlı A, A K, editors. Evcil Hayvanlarda Meme Hastalıkları. Malatya, Türkiye: Medipres; 2016. p.149-259.

[10] Howard A, Zhmoginov A, Chen LC, Sandler M, Zhu M. Inverted residuals and linear bottlenecks: Mobile networks for classification, detection and segmentation. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2018 June; Salt Lake City, USA: IEEE; 2018. doi: https://doi.org/gfxgjz

[11] Tan M, Le Q. EfficientNet: Rethinking model scaling for convolutional neural networks. Proceedings of the International Conference on Machine Learning (ICML); 2019 June 9-15; Long Beach, California, USA: PMLR; 2019. doi: https://doi.org/ht8s

[12] Tan M, Le Q. EfficientNetV2: Smaller models and faster training. Proceedings of the International Conference on Machine Learning (ICML); 2021 July 18-24; Virtual Conference: PMLR; 2021. doi: https://doi.org/rfrx

[13] Chollet F. Xception: Deep learning with depthwise separable convolutions. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2017 July 21-26; Honolulu, USA: IEEE; 2017. doi: https://doi.org/gfxgtm

[14] Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z. Rethinking the inception architecture for computer vision. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2016 June 27-30; Las Vegas, USA: IEEE; 2016. doi: https://doi.org/gftjd7

[15] Zoph B, Vasudevan V, Shlens J, Le QV. Learning transferable architectures for scalable image recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2017 July 21-26; Honolulu, USA: IEEE; 2017. doi: https://doi.org/gpmnmc

[16] Szegedy C, Ioffe S, Vanhoucke V, Alemi A. Inception-v4, Inception-ResNet and the impact of residual connections on learning. Proceedings of the AAAI Conference on Artificial Intelligence; 2017 Feb 4-9; San Francisco, USA. Palo Alto: AAAI Press. 2017; 31(1):11231. doi: https://doi.org/gq9mjs

[17] Liu Z, Mao H, Wu CY, Feichtenhofer C, Darrell T, Xie S. A ConvNet for the 2020s. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR); 2022 June 18-24; New Orleans, USA: IEEE; 2022. doi: https://doi.org/gq9m63

[18] Sunder HA, Gupta D, Singh R, Singh S, Randhawa C. Ultrasonographic changes in teat and supramammary lymph nodes in dairy cows affected with clinical mastitis. Haryana Vet. [Internet]. 2022 [cited 20 Mar 2026]; 61(SI):68-71. PMID: 27175155. Available in: https://goo.su/vaNqv

[19] Mateen A, Aslam S, Abdullah OM, Qaisrani SA, Aziz A, Sajid SM, Din AMU, Khalique MA, Ahmed G. Ultrasound technology in the diagnosis and prognosis of mastitis in dairy cattle: Advancements, applications, and future directions. Indus J. Biosci. Res. [Internet]. 2025; 3(6):484-493. doi: https://doi.org/rfr2