



Artificial Intelligence for Enhancing Veterinary Healthcare: An Experiment

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ABSTRACT

Background: The use of machine learning (ML) in veterinary medicine has gained significant attention, particularly for the early detection and classification of animal diseases. For example: lumpy Skin Disease (LSD) in cattle is one such condition that poses a substantial threat to livestock health. Traditional diagnostic methods can be labor-intensive and time-consuming. Therefore, leveraging ML techniques for automated disease detection could improve diagnostic efficiency and accuracy.

Methods: In this study, a dataset comprising images of cattle from four breeds-Vechur, Swiss Holstein, Jersey and Ponwar-was collected to train a DenseNet-121 Convolutional Neural Network (CNN) model for identifying and classifying LSD in cattle. The dataset included both LSD-affected and non-affected cattle images, ensuring balanced representation across different breeds, ages and severity levels. Image preprocessing techniques such as resizing, normalization and data augmentation were applied to prepare the data for model training. The DenseNet-121 architecture was employed, utilizing a pretrained ImageNet model as the feature extractor, with additional layers for binary classification.

Result: The model achieved excellent performance, with training accuracy reaching 99.76% and validation accuracy of 92.17%. The precision, recall and F1-score for the "Lumpy" class were 96.43%, 81.82% and 88.52%, respectively, while the "Normal" class had a precision of 92%, recall of 98.57% and F1-score of 95.17%. The overall accuracy of the model was 93.2%. Additionally, the model achieved an AUC score of 0.96 for both classes, indicating a high ability to distinguish between "Lumpy" and "Normal" cattle. These results highlight the potential of ML-based methods in enhancing the efficiency and accuracy of veterinary disease diagnostics.

Key words: Animal health, Artificial intelligence, Convolutional neural network (CNN), Machine learning.

INTRODUCTION

Artificial intelligence (AI) has been a potent force in transforming the approach toward predicting and diagnosing animal diseases (Appleby and Basran, 2022). As comprehension of AI applications in healthcare expands, there is an increasing acknowledgment of its capacity to improve veterinary practices, providing inventive resolutions to long-standing difficulties in animal healthcare (Bohr and Memarzadeh, 2020). The convergence of AI and veterinary medicine offers a distinct chance to enhance disease prediction and diagnosis accuracy, as well as redefine the extent of preventive care and treatment approaches (Ezanno *et al.*, 2021). This study aims to thoroughly investigate the current state of AI in veterinary healthcare, with a particular emphasis on its use in predicting and diagnosing animal diseases.

Veterinary healthcare has depended on a blend of clinical expertise, diagnostic examinations and medical records to detect and treat animal diseases (Cassidy *et al.*, 2017). Veterinarians must have a sharp eye for clinical observation, accurate evaluation of laboratory tests and empirical knowledge to diagnose and treat diseases (Hobson-West and Jutel, 2020). Nevertheless, the drawbacks associated with traditional approaches, such as lengthy procedures and subjective assessments, less precise diagnosis and overreliance on symptomatic treatment have prompted the incorporation of AI technology into the field of veterinary medicine (Ahuja, 2019). In addition,

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like any other medical field, the veterinary field can sometimes be resistant to adopting new technologies and methodologies. This resistance may stem from a lack of awareness, training, or a preference for familiar practices. Traditional veterinary care often leans towards a reactive approach, addressing health issues as they arise (Bazzi, 2022). Insufficient emphasis on preventive measures such as vaccination programs, routine screenings and nutritional planning has been observed, which could help avoid diseases altogether (Bohr and Memarzadeh, 2020). This lack of emphasis is also affecting the physical health of veterinarians, who are at risk of contracting zoonotic

diseases due to their proximity to animals. Zoonotic diseases are a leading cause of human illnesses (Kinnunen *et al.*, 2022; Cho, 2024; Hai and Duong, 2024; Semara *et al.*, 2024; Maltare *et al.*, 2023; Bagga *et al.*, 2024; AlZubi, 2023).

The traditional diagnostic and treatment methods can be resource-intensive, posing barriers for communities with limited resources. Additionally, certain traditional medications and treatments, like overused antibiotics in animal agriculture, can lead to environmental consequences, such as antibiotic resistance and pollution (Kinsella *et al.*, 2009). Hence, there is an urgent need for immediate efforts to address the current state of animal healthcare to ensure its sustainability. Recently, artificial intelligence (AI) has emerged as a promising tool in veterinary science, contributing significantly to advancements across various facets of animal healthcare.

This research paper aims to delve into the intricate world of AI applications in animal disease prediction and diagnosis, encompassing a comprehensive review of the current landscape, identification of challenges and limitations and exploration of future directions.

Current state of veterinary healthcare

Veterinary healthcare plays a pivotal role in preserving and sustaining animal life and enhancing the well-being of human populations by improving rural livelihoods and nutrition. Additionally, it contributes to mitigating global health crises by proactively addressing risks such as the emergence of pandemic diseases, antimicrobial resistance, food contamination and environmental health issues at their source.

Veterinarians employ a multifaceted approach to diagnose and treat illnesses in animals. Beginning with a thorough clinical examination to assess physical health and symptoms, they utilize diagnostic imaging, laboratory tests and microscopic analysis of tissue samples for a comprehensive understanding (Evason *et al.*, 2021). Genetic testing, allergy testing and specialized diagnostics for infectious diseases aid in identifying underlying causes (Johnson *et al.*, 2021). Treatment plans, which may include medications, surgery, dental procedures and nutritional management, are tailored to the specific condition.

However, preventive care, which involves taking proactive measures to maintain the health of animals and detect potential issues early on, is the cornerstone of animal healthcare (Evason *et al.*, 2021). This approach aims to prevent diseases, identify risk factors and address health concerns before they become more serious. Regular check-ups, vaccinations and parasite control are crucial in preventing diseases and maintaining overall animal health.

The diagnosis of animal diseases primarily depended on clinical signs and confirmation made through a limited range of laboratory tests and microbiological cultures. This was then improved with the inclusion of radiography and ultrasound. However, it still takes several days for confirmation and sometimes requires outsourcing or

referral to specialists (Perera *et al.*, 2022). Any delay in diagnosis can cause significant damage to public health and industries, especially in the case of infectious diseases. Early detection of diseases allows for timely intervention and improves treatment outcomes (Evason *et al.*, 2021).

However, there are many challenges faced by veterinarians in diagnosing and treating animals such as difficulty in obtaining accurate information due to limited communication with animals, stress induced in animals during procedures, financial constraints for pet owners and limited resources in certain regions (Bomzon, 2011; McKenzie, 2014; Pun, 2020). Ethical dilemmas arise when balancing the best interests of the animal with owner preferences and financial considerations. Zoonotic risks and the need for owner compliance further complicate the veterinary landscape. Staying abreast of rapid technological advances and managing the emotional toll of difficult cases also contribute to the challenges faced by veterinarians. Overcoming these obstacles requires ongoing professional development, effective communication, preventive care emphasis and collaboration within the veterinary community to provide optimal and compassionate care to animals.

Veterinary medicine is now becoming specialized, with veterinarians focusing on specific areas of expertise, such as internal medicine, surgery, oncology and exotic animal medicine. This specialization allows for more in-depth knowledge and expertise in specific areas, leading to improved diagnostic accuracy and treatment efficacy (Rosol *et al.*, 2009). In addition, the One Health approach which recognizes the interconnectedness of human, animal and environmental health, emphasizes the need for a collaborative approach to address health challenges that affect multiple species. By working together, veterinarians, physicians, veterinary scientists and public health officials can better understand and control the spread of zoonotic diseases and promote the overall health of humans, animals and the environment (Velazquez-Meza *et al.*, 2022). Utilizing artificial intelligence as a tool for mechanistic epidemiological modeling is illustrated in Fig 1.

The field of veterinary medicine has witnessed significant advancements in recent years, leading to improved diagnostic tools, more effective treatments and a greater understanding of animal diseases (Buller *et al.*, 2020). Technological innovations, such as artificial intelligence (AI) and machine learning, are being harnessed to analyze medical images, identify patterns and develop personalized treatment plans. Additionally, regenerative medicine holds promise for repairing damaged tissues and organs, offering new therapeutic options for previously incurable conditions (Haleem *et al.*, 2021). These innovative approaches, coupled with traditional practices, are paving the way for a more comprehensive and effective veterinary healthcare system. However, these emerging approaches also have limitations. Telemedicine may not be suitable for all cases, especially those requiring hands-on examinations or

specialized procedures. AI-powered tools may require extensive data training and validation to ensure their accuracy and reliability. Precision medicine relies on comprehensive genetic and environmental information, which may not always be readily available. Regenerative medicine is still in its early stages of development and its long-term safety and efficacy require further research and clinical trials (Johnson *et al.*, 2021).

AI application in veterinary medicine

Artificial intelligence (AI) is rapidly transforming the field of animal healthcare, introducing groundbreaking tools and techniques that are enhancing diagnostic accuracy, streamlining treatment planning and optimizing animal well-being. AI applications are revolutionizing various aspects of veterinary care, offering a comprehensive and holistic approach to animal health.

AI-powered behavior analysis and modification

AI is providing valuable insights into animal behavior, enabling veterinarians to identify and address behavioral issues such as anxiety, aggression and stress. AI-powered tools can analyze animal behavior patterns, vocalizations and movement patterns to detect subtle signs of behavioral problems. This information can be used to develop personalized behavior modification plans, improve animal

welfare and reduce the risk of behavioral problems (Aguilar-Lazcano *et al.*, 2023).

Remote patient monitoring and early intervention

AI-enabled wearable devices and sensors are transforming animal healthcare by providing real-time data on animal health parameters. These devices can collect data on heart rate, activity levels, sleep patterns and other vital signs, allowing veterinarians to remotely monitor animal health and detect potential problems early. This remote monitoring capability enables timely intervention, preventing the worsening of health conditions and improving overall animal well-being (Mitro *et al.*, 2023). With advancements in telecommunications technology, telemedicine has become more accessible in veterinary care. Veterinarians can now conduct remote consultations, provide guidance on animal health concerns and even prescribe medications without the need for in-person visits. This technology is particularly beneficial for rural areas with limited access to veterinary services. Smith *et al.* (2022) conducted surveys with 17 access to veterinary care organizations, 516 veterinarians and clinic employees and 1009 animal owners. Their research highlighted the COVID-19 pandemic's effects, exposing both fresh and worsened difficulties in obtaining and providing veterinary care. Widmar *et al.* (2020) reported that there are numerous

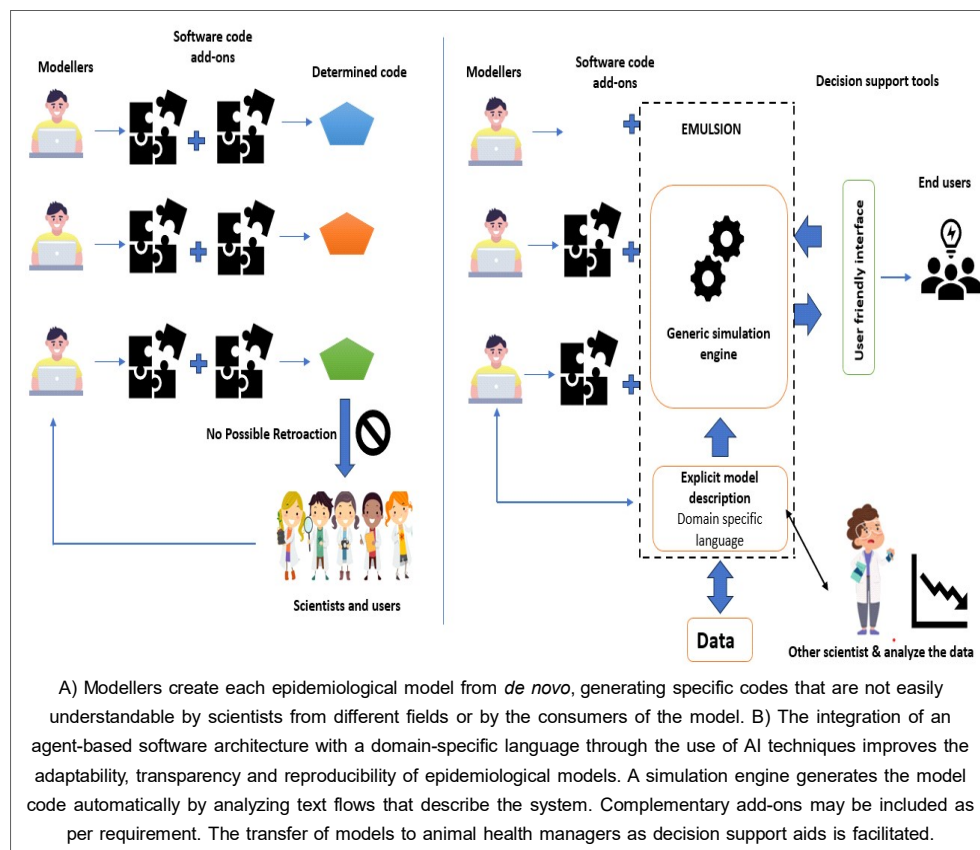


Fig 1: The use of Artificial Intelligence as a tool in mechanistic epidemiological modeling.

benefits to veterinary telemedicine for both pet owners and their animal friends. These include avoiding children visiting the clinic, bringing large, nervous, or fearful animals, improving the accessibility of veterinary services in remote areas, providing clients with quick access to advice or triage to decide whether an in-person visit is required, saving time and making use of more flexible consultation hours. They also found that dog owners in the United States were willing to pay an extra \$38.04 or \$13.38, respectively, for a telemedicine consultation with either their primary care veterinarian or another veterinarian in the vicinity. For cat owners, these figures were \$38.12 and \$12.74, respectively. (Widmar *et al.*, 2020).

Cloud computing for data storage and analysis

Cloud computing provides scalable and cost-effective solutions for storing and analyzing large volumes of veterinary healthcare data. By leveraging cloud-based platforms, veterinarians can access medical records, imaging studies and research findings from anywhere with an internet connection, facilitating collaborative research and decision-making.

Bioinformatics for Disease Surveillance and Epidemiology

Bioinformatics tools enable the analysis of large-scale genomic and epidemiological data to track disease outbreaks, monitor antimicrobial resistance and identify emerging infectious diseases in animal populations. These tools play a crucial role in public health surveillance and disease control efforts. Tran *et al.* (2024) provided an overview of bioinformatics applications in preventive medicine and epidemiology, showcasing their potential and future prospects.

MATERIALS AND METHODS

Monitoring animal health like cattle using ML involves a multidisciplinary approach that integrates data collection, feature extraction, model training and real-time analysis. The methodology typically follows these key steps.

Data collection

For the ML algorithm, a dataset included images of cattle from four breeds: Vechur, Swiss Holstein, Jersey and Ponwar was created to train and evaluate a DenseNet121-CNN model for identifying and categorizing lumpy skin disease (LSD) in cattle. Data collection, guided by cattle farming specialists, included both LSD and non-LSD skin images to ensure balanced representation. A total of 450 Vechur cattle, aged 1-9 years and over 9 years, were represented, with 70% female and 30% male animals. They covered all severity categories, including mild, moderate and severe lesions. The Swiss Holstein breed contributed 803 cattle within the same age range and gender distribution. Jersey cattle, totaling 500, were exclusively female, spanning similar age groups. Lastly, 450 Ponwar cattle were included, also aged 1-9 years and over 9 years, with a 70% female and 30% male ratio.

The dataset was split 80% for training and 20% for validation. Image preprocessing.

The images were loaded using the PIL (Python Imaging Library), ensuring compatibility and consistency in format. Each image was resized to 224×224 pixels to match the input size required by the DenseNet-121 model. To enhance model generalization, pixel values were normalized by scaling them to the range $[0, 1]$. Additionally, data augmentation techniques such as random flipping, rotation and zooming were applied to the training set using TensorFlow's built-in augmentation layer. Finally, class labels were converted into a one-hot encoded format, enabling the model to learn classification effectively.

Model architecture

The DenseNet-121 deep CNN was employed for classification, using a pretrained ImageNet model as its feature extractor (Fig 2). The DenseNet-121 architecture consists of densely connected convolutional layers, enhancing gradient flow and feature propagation. In this study, the pretrained base model was used without its original classification head and additional layers were appended to tailor it for the binary classification task. These included a Global Average Pooling layer, a fully connected dense layer with 512 units and ReLU activation, followed by a Dropout layer (0.5 dropout rate) to prevent overfitting and a final softmax output layer for binary classification. The model was trained using the Adam optimizer (learning rate = 0.0001) with categorical cross-entropy loss to optimize performance.

Training and validation

The proposed model is trained on the part of the collected datasets, with careful adjustment of their settings and optimization (de Lacy *et al.*, 2022). A separate validation

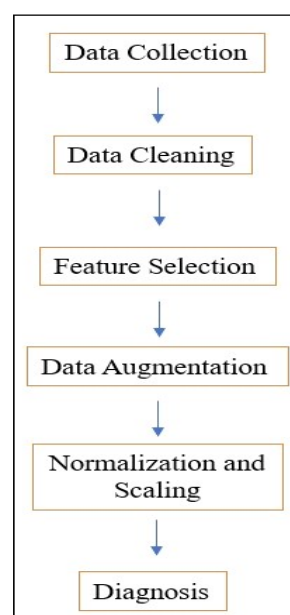


Fig 2: Data preprocessing process for animal disease.

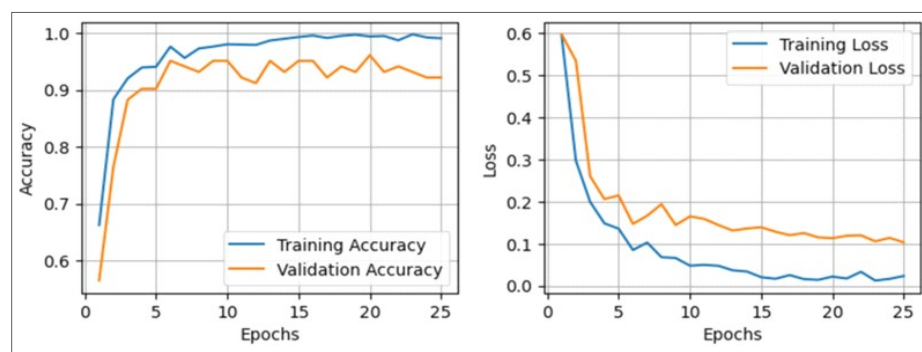


Fig 3: Accuracy and loss terms over epochs.

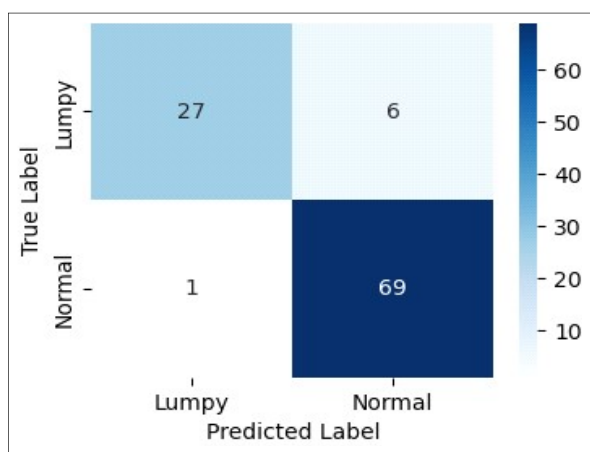


Fig 4: Confusion matrix.

dataset is used to check how well the models work in different situations. This process is repeated to improve the models, aiming for the best performance in predicting and diagnosing animal diseases (Patil and Rane, 2021).

RESULTS AND DISCUSSION

The results obtained after training, validation and testing are summarized in the following section. The training and validation accuracy, along with the corresponding loss values, were recorded over 25 epochs to assess model performance. The training accuracy started at 66.23% in the first epoch and steadily increased, reaching 99.76% in the final epoch. Similarly, the validation accuracy improved from 56.47% to 92.17%, indicating effective learning. The training loss showed a consistent decline from 0.5944 to 0.0124, while the validation loss decreased from 0.5978 to 0.1033, demonstrating reduced classification errors. The plotted accuracy and loss curves in Fig 3 provided insights into the model's convergence, stability and potential overfitting trends.

In this study, the performance of the classification model was evaluated using a confusion matrix, which provides a detailed breakdown of the model's predictions compared to the actual labels (Fig 4). The confusion matrix, depicted in a heatmap, shows the true positive, false positive, true

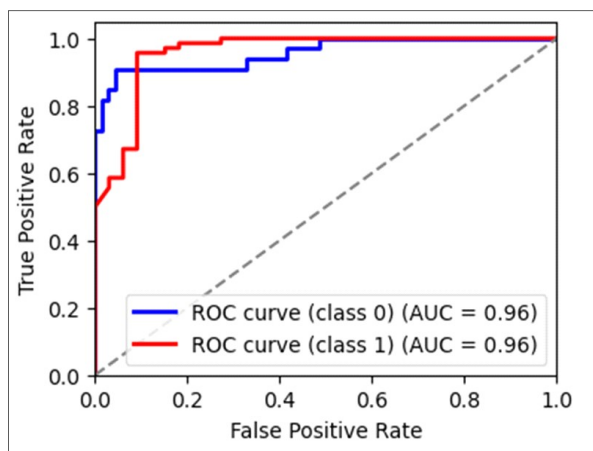
negative and false negative values. For the binary classification task, the two class labels "Lumpy" and "Normal" were used. The heatmap, generated using Seaborn, visualizes these values, with the x-axis representing the predicted labels and the y-axis representing the true labels. The matrix is annotated with integer values to indicate the number of instances for each category. The color intensity, represented in shades of blue, highlights the correct and incorrect classifications, providing a clear and intuitive understanding of the model's performance.

The results, as shown in the confusion matrix, indicate that the model performs well in classifying the "Lumpy" and "Normal" instances. Specifically, for the "Lumpy" class, the model correctly identified 27 instances as "Lumpy" (True Positive) and misclassified 6 instances as "Normal" (False Negative). For the "Normal" class, it correctly identified 69 instances as "Normal" (True Positive) and misclassified 1 instance as "Lumpy" (False Positive). These results demonstrate the model's overall accuracy in distinguishing between the two classes, with a minimal number of misclassifications.

The performance of the model is evaluated using several key metrics: Precision, Recall, F1-Score and Support for the two classes, "Lumpy" and "Normal" (Table 1). For the "Lumpy" class, the model has a precision of 96.43%, meaning that 96.43% of the instances predicted as "Lumpy" were correct, though its recall is 81.82%, indicating that the model correctly identified 81.82% of the actual "Lumpy" instances. The F1-score for "Lumpy" is 0.8852, reflecting a good balance between precision and recall. In contrast, for the "Normal" class, the precision is 92% and the recall is very high at 98.57%, meaning the model effectively detects most "Normal" instances. The F1-score for "Normal" is 0.9517, suggesting excellent balance. The accuracy of the model is 93.2%, indicating that it correctly classified 93.2% of the total instances. The macro average, which treats both classes equally, shows a precision of 94.21%, recall of 90.19% and F1-score of 91.85%, while the weighted averages, accounting for the class distribution, are slightly higher with a precision of 93.42%, recall of 93.20% and F1-score of 93.04%. These metrics demonstrate that the model

Table 1: Classification matrices.

Class	Precision	Recall	F1-Score	Support
Lumpy	0.9643	0.8182	0.8852	33
Normal	0.9200	0.9857	0.9517	70
Accuracy			93.2%	
Macro avg	0.9421	0.9019	0.9185	103
Weighted avg	0.9342	0.932	0.9304	103

**Fig 5:** ROC(AUC) curve.

performs well overall, with a slight bias toward the “Normal” class due to its larger number of instances.

Further, the model's performance was evaluated using the ROC curve and AUC score (Fig 5). The AUC for both the “Lumpy” and “Normal” classes is 0.96. This indicates that the model is highly effective at distinguishing between the two classes.

CONCLUSION

Exploring sophisticated AI approaches, developing uniform standards and incorporating AI education into veterinary curricula emerge as key milestones as we move forward. This study demonstrated the successful application of machine learning for the detection and classification of Lumpy Skin Disease in cattle. The DenseNet-121 model showed excellent classification performance, achieving high accuracy, precision, recall and F1-scores for both “Lumpy” and “Normal” classes. The ROC curve and AUC score of 0.96 further affirmed the model's robust ability to differentiate between the two classes. Looking ahead, the integration of AI in veterinary medicine holds great potential for improving disease detection and animal health monitoring. Future advancements should focus on the development of uniform standards and the incorporation of AI into veterinary education. By adopting a One Health approach, AI could play a pivotal role in disease prevention and control, ultimately improving animal welfare and healthcare.

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Data availability statement

The database generated and/or analysed during the current study are not publicly available due to privacy, but are available from the corresponding author on reasonable request.

Declarations

Author declare that all works is original and this manuscript has not been published in any other journal.

Conflict of interest

The authors declare that they have no conflict of interest.

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