Egypt. J. Vet. Sci., pp. 1-6

Egyptian Journal of Veterinary Sciences

https://ejvs.journals.ekb.eg/

[A Review Article]

Artificial Intelligence Advances in Equine Medicine and Breeding

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Abstract

EQUINE health and breeding are vital areas where emerging technologies, particularly artificial intelligence (AI), are beginning to offer innovative solutions and applications. This study aimed to analyze recent literature regarding the applications, accuracy, and challenges of AI in equine health and breeding. In disease diagnosis, AI technologies, such as marker-less pose estimation, have proven effective in detecting lameness, accurately distinguishing between healthy horses and those with forelimb or hind limb problems. AI-driven deep learning algorithms have significantly enhanced the diagnosis of exercise-induced pulmonary hemorrhage (EIPH), consistently surpassing human annotators. In gastrointestinal health, AI models are excelling in classifying colic severity and determining the need for surgical intervention, resulting in improved treatment outcomes. AI is also transforming equine breeding by predicting breeding values based on genomic and phenotypic data. For instance, artificial neural networks (ANN) and support vector regression (SVR) have been utilized to forecast gait traits and optimize breeding strategies. Additionally, AI applications in equine imaging, such as video motion magnification for embryo selection, are enhancing reproductive efficiency. Regarding performance prediction, AI models have demonstrated high accuracy in for recasting race outcomes. Separately, monitoring grazing behaviors and food intake contributes to effective control of horses in pasture. However, challenges remain, including data quality issues, rresistance to integrating AI systems, and ethical concerns. The future of AI in equine care is promising, especially with the potential integration of AI and Internet of Things (IoT) devices for real-time monitoring and personalized medicine, which could greatly enhance equine health and performance.

Key words: artificial intelligence, farming, equine, health, performance.

Introduction

Artificial intelligence (AI) involves the use of algorithms to filter data, identify complex patterns, and perform decision-making tasks [1, 2]. Despite often being perceived as a recent innovation, AI has a long history, beginning in the 1950s, and has since rapidly evolved from a conceptual framework into a transformative technology that impacts many fields, including healthcare, engineering, agriculture, and education [3]. By enabling machines to learn from data, recognize patterns, and make decisions, AI serves as a powerful tool for solving complex challenges. Its integration into both human and veterinary medicine marks a significant advancement in utilizing technology to enhance care, improve outcomes, and streamline processes [4, 5].

Veterinary care, while historically slower to adopt advanced technologies compared to human healthcare, is now beginning to embrace AI as a means to address its unique challenges. Veterinary practitioners face a wide range of health and welfare issues, dealing with diverse species and non-verbal patients, from individual companion animals to large agricultural populations. AI provides tailored solutions to these complexities, enhancing diagnostics, predictive analytics, and more precise care management [6, 7].

Diagnostic imaging, for instance, has been significantly improved through AI, allowing more accurate identification of orthopedic conditions and internal diseases. Additionally, AI-based monitoring tools are transforming livestock management by enabling farmers to track herd health, optimize

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(Received 26 March 2025, accepted 17 June 2025)
DOI: 10.21608/ejvs.2025.371353.2735

feeding practices, and predict disease outbreaks [5, 6]. In equine care, AI technologies are being used to improve the detection and treatment of common conditions such as lameness and colic, as well as to enhance performance monitoring and breeding strategies [8].

This review aimed to explore the possible applications, benefits, and limitations of AI in equine medicine and breeding. By synthesizing existing literature, it identifies research gaps and provides insights into the future potential of AI in advancing equine health and breeding management.

Material and Methods

This review aimed to explore the current landscape of AI applications in equine breeding and medicine by analyzing relevant peer-reviewed articles identified through databases such as PubMed, Google Scholar, and ScienceDirect. For this purpose, various combinations of keywords were used, including *"artificial intelligence," "equine medicine," "machine learning," "horse breeding,"* and *"veterinary AI."* Studies were included if they specifically focused on AI applications in areas such as genetic selection, performance prediction, reproduction, breeding, treatment optimization, or equine health diagnostics. Articles that addressed general veterinary AI without a specific focus on the equine context were excluded. Each article was examined for its objectives, methodology, findings, limitations, and future research directions. Additionally, ethical considerations and potential risks associated with AI implementation in equine care were reviewed.

Results and discussion

Machine Learning for Lameness Detection

Pose estimation is a technology commonly used to analyze limb and body movements without the need for attaching devices to the body [9]. This program was tested on 22 horses with lameness and included a control group of eight healthy horses. Based on the trajectory of the horse's movement, the software successfully distinguished between healthy horses and those exhibiting either forelimb or hind limb lameness [10]. Recently, a marker-less artificial intelligence (AI) motion-tracking system has been developed for lameness assessment. A study was conducted to compare this system with an inertial measurement unit system and with clinical examinations to evaluate the level of agreement and accuracy of both systems in relation to visual assessments. The findings showed that the clinical examination was effective in detecting locomotor asymmetries with both systems. The AI motion tracking system identified a greater number of limbs as asymmetric. The highest level of agreement was observed for forelimb movement on a straight, hard surface, while the lowest agreement was noted for pelvic movement on a straight, soft surface. This discrepancy is likely due to the challenges in assessing hind limb asymmetry [11].

AI for Equine Respiratory Diseases

Exercise-induced pulmonary haemorrhage (EIPH) is a serious respiratory condition affecting sport horses. It is diagnosed using the total hemosiderin score (THS) derived from broncho-alveolar lavage fluid (BALF) samples. A study aimed to evaluate the diagnostic accuracy and reproducibility of human annotators and to validate a deep learning algorithm for THS assessment [12]. This study involved analyzing iron-stained cytological slides from 52 equine BALF samples by ten different annotators. Their THS evaluations were compared to a ground truth dataset, averaged annotator scores, and chemical measurements of iron. The results showed significant inter-observer variability among the annotators, mainly due to systematic grading errors. By standardizing the grading based on the ground truth, the measurement variance was reduced by 87.7%. In contrast, the deep learning algorithm demonstrated greater consistency and accuracy, achieving an accuracy of 92.3% in diagnosing EIPH (with THS values less than or greater than or equal to 75), compared to only 75.7% accuracy for human annotators. Additionally, the algorithm showed a similar correlation with chemical iron measurements. The study emphasizes the advantages of using deep learning algorithms to enhance the reproducibility and practicality of THS assessments. It also proposes a diagnostic uncertainty interval of 40 to 110, as THS values within this range exhibit insufficient reproducibility for a reliable EIPH diagnosis [12].

Monitoring Models for Colic

Eerdekens et al. (2024) [13] developed a software algorithm designed to identify early indicators of gastrointestinal discomfort in horses by detecting signs of colic and assessing pain levels. In their study, transient colic was induced in eight mares, and veterinarians assigned pain scores to classify the severity of the colic. They classified behaviours—both normal and 10 related to pain—using accelerometric data and video analysis, ultimately calculating an activity index. This machine-learning model achieved an accuracy of 91.2% in detecting colic and 93.8% in differentiating severity levels, demonstrating high precision in classifying pain-related behaviours. Additionally, Fraiwan et al. (2020) [14] applied machine learning algorithms to predict the necessity of surgery and the survivability of horses suffering from acute abdomen [colic] using basic clinical data. Their models achieved 76% accuracy in predicting the need for surgery and 85% accuracy in estimating survivability [14].

Breeding Value Prediction

Bussiman et al. (2024) [15] explored the use of machine learning to predict breeding values for five gait traits in Campolina horses (dissociation, comfort, style, regularity, and development). Using over 5,000 phenotypic records and a 14-generation pedigree of 107,951 horses, they applied artificial neural networks (ANN), random forest regression (RFR), and support vector regression (SVR) to adjusted phenotypes derived from fixed and multiple-trait models (MTM). The breeding values from MTM served as the target. All models showed similar accuracy, with R^2 values ranging from 0.81 (RFR and SVR) to 0.83 (ANN). Despite its higher accuracy, the ANN model displayed greater bias and dispersion, particularly for younger animals [15].

Identifying SNP Markers

The ability to accurately determine a horse's breed using a small set of discriminant SNP markers is one of the most significant practical applications of genomic data. To identify informative SNP markers for accurately classifying unknown samples, Manzoori et al. (2023) [16] used artificial neural networks (ANN), including Deep Neural Networks (DNN), and feature selection methods (Garson and Olden) to analyze data from 795 animals across 37 breeds genotyped with the Illumina SNP 50k BeadChip. They identified subsets of SNP markers that achieved a 70% success rate based on log-likelihood ratio thresholds. The DNN method was the most accurate, reaching 93% accuracy under stringent conditions. Validation with 120 animals from eight breeds confirmed the markers' effectiveness, with all samples correctly assigned to their populations. The study highlights DNN as a powerful tool for selecting discriminant SNP markers, enabling efficient and accurate population assignment with fewer markers [16].

Optimizing Embryo Transfer Programs

Hickerson (2022) [17] discusses the evaluation and selection of embryos for transfer into recipient mares to improve pregnancy rates. The study highlights advanced techniques such as video motion magnification (VMM) for assessing embryo viability. A total of 41 equine embryos, graded as Quality 1 or 2 according to International Embryo Transfer Society (IETS) guidelines, were analyzed for their morphokinetic activity. VMM amplified video data by 300 times, allowing previously imperceptible morphological changes to be measured accurately. The parameters assessed included the area of the inner cell mass (ICM), the thickness of the zona pellucida (ZP), the perivitelline space, and variations in axis dimensions. By integrating morphokinetic evaluation, this study demonstrates the potential of AI-enhanced techniques to provide more reliable metrics for selecting viable equine embryos, ultimately improving reproductive efficiency and outcomes [17].

AI in Performance Prediction for Sport Horses

Gupta and Singh (2023) [18] examined the application of data mining techniques to predict horse race outcomes. The author utilized a diverse range of parameters, including horse-related factors (such as past performance, age, weight, and speed), jockey-related factors (including experience, past performance, and win rates), and race-related factors (such as track conditions, weather, distance, and competition level). The study achieved an impressive accuracy rate of approximately 90% across all models, demonstrating their effectiveness. In a separate study focused on detecting fatigue in sport horses [18]. Darbandi et al. (2023) [19] developed a machine learning models using inertial sensors to classify strides as either non-fatigue or fatigue. Their research demonstrated that biomechanical features (including stance duration, swing duration, and limb range of motion) can serve as reliable indicators of fatigue. The fatigue classification model achieved high accuracy across both walk and trot gaits [19]. In related research aimed to improve exercise management and prevent injuries in sport horses, a non-invasive monitoring system was developed using inertial sensors mounted on the horse’s lower limbs and trunk. This system collects critical gait and limb-load data during regular training sessions, providing detailed measurements of movement and force distribution. The approach offers valuable insights into how training affects each horse and how environmental conditions influence performance. By analyzing these parameters, trainers can better understand individual responses to exercise, allowing for optimized training regimens that enhance performance while minimizing injury risks. This method represents a practical tool for advancing equine welfare and long-term athletic health in competitive settings [20].

Horse Foraging Behaviour

Nunes et al. (2021) [21] introduced a computational tool for monitoring grazing behaviour in horses, utilizing wearable sensors and deep learning techniques to identify chewing and biting events. They collected audio and video data using a micro camera equipped with a microphone, which was then pre-processed to train a recurrent neural network (RNN) that included a long short-term memory (LSTM) layer. Post-processing methods were employed to enhance the detection of events. The system demonstrated an accuracy of 88.64% for identifying bites and 94.13% for identifying chews. This tool provides valuable insights into grazing behaviour, such as bite rate, mass, and duration, allowing for improved pasture management and better modeling of foraging behaviour to predict animal performance and pasture usage [21].

Challenges and Limitations

Data Availability and Quality

The availability and quality of data present significant obstacles to the use of AI in horse care and breeding. Large datasets are essential for training many AI models; however, in the equestrian industry, such datasets are sometimes unavailable or inadequate. Additionally, data may be collected in different settings, leading to irregularities that can negatively impact the accuracy of AI predictions [22, 23].

Resistance to Adoption

Although AI technologies offer numerous benefits, the horse industry remains somewhat resistant to their adoption, particularly among veterinarians and breeders who are accustomed to traditional methods. Embracing AI requires a shift in mindset and often necessitates investment in new tools and training. To facilitate broader implementation, it will be crucial to address concerns regarding the reliability and transparency of AI systems [24, 25].

Ethical Considerations

As AI technology begins to be used in horse treatment and breeding, it is essential to address the ethical issues that arise. Important concerns include data privacy, the risk of excessive reliance on automated systems, and the welfare implications of breeding decisions informed by AI. To ensure the responsible use of these technologies, developing ethical standards for AI applications in the equestrian sector will be crucial [26, 27, 28].

Future Directions

AI Integration with Internet of Things (IoT)

Future developments may lead to closer integration of AI with IoT devices in the fields of equestrian breeding and therapy. Sensors and smart devices can continuously collect data on the environment and health of horses. AI systems can then use this data to perform real-time analysis. As a result, certain horses may receive more tailored care and management strategies [29, 30].

AI in Personalized Medicine for Horses

Equine medicine is increasingly adopting the concept of individualized care, similar to trends in human healthcare. AI-powered tools can analyze a horse's unique genetic, environmental, and health information to provide specific medical treatment and preventive measures. This approach can potentially reduce the risk of illness and injury while improving each horse's performance and overall health [31].

Conclusion

Integrating AI technology into equine practices and breeding programs can maximize sport horse performance, improve breeding outcomes, and enhance horse welfare. However, to fully benefit from AI in the equine industry, we must address challenges related to technology adoption, data quality, and ethical considerations. The successful implementation of AI in this sector will depend on ongoing research and collaboration among data scientists, breeders, and veterinarians.

Acknowledgments

Not applicable.

Funding statement

This study didn't receive any funding support

Declaration of Conflict of Interest

The authors declare that there is no conflict of interest.

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تطورات الذكاء الاصطناعي في طب وتربية الخيول

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الملخص

تُعدّ صحة الخيول وتربيتها من المجالات الحيوية التي بدأت فيها التقنيات الناشئة، وخاصةً الذكاء الاصطناعي، بتقديم حلول مبتكرة. تهدف هذه الدراسة إلى تحليل منهجي للدراسات الحديثة المتعلقة بتطبيقات الذكاء الاصطناعي ودقته وتحدياته في صحة الخيول وتربيتها. في مجال تشخيص الأمراض، أثبتت تقنيات الذكاء الاصطناعي، مثل تقدير الوضعية بدون علامة (marker-less pose estimation)، فعاليتها في الكشف عن العرج، والتمييز بدقة بين الخيول السليمة وتلك التي تعاني من مشاكل في الأطراف الأمامية أو الخلفية. وقد حسّنت خوارزميات التعلم العميق المدعومة بالذكاء الاصطناعي تشخيص النزيف الرئوي الناتج عن التمرين (EIPH) متفوقة بشكل ملحوظ على الاطباء البيطريين. فيما يخص صحة الجهاز الهضمي، تتفوق نماذج الذكاء الاصطناعي في تصنيف شدة المغص وتحديد الحاجة إلى التدخل الجراحي، مما يؤدي إلى تحسين نتائج العلاج. كما يُحدث الذكاء الاصطناعي نقلة نوعية في تربية الخيول من خلال التنبؤ بقيم التربية بناءً على البيانات الجينومية والظاهرية. على سبيل المثال، استُخدمت الشبكات العصبية الاصطناعية (ANN) وانحدار ناقلات الدعم (SVR)للتنبؤ بخصائص المشي وتحسين استراتيجيات التربية. بالإضافة إلى ذلك، تُحسّن تطبيقات الذكاء الاصطناعي في مجال الأشعة السينية من الكفاءة التناسلية مثل تكبير حركة الفيديو لاختيار الأجنة. فيما يتعلق بالتنبؤ بالأداء، أظهرت نماذج الذكاء الاصطناعي دقة عالية في التنبؤ بنتائج سباقات الخيول. وبشكل منفصل، تُسهم مراقبة سلوكيات الرعي وتناول الغذاء في التحكم الفعال في الخيول في المراعي. ومع ذلك، لا تزال هناك تحديات، بما في ذلك مشكلات جودة البيانات، العزوف عن تقبّل تقنيات الذكاء الاصطناعي، والاعتبارات الأخلاقية. إن مستقبل الذكاء الاصطناعي في رعاية الخيول واعد، لا سيما مع إمكانية دمج أجهزة الذكاء الاصطناعي وإنترنت الأشياء (IoT) للمراقبة الآنية والطب الشخصي، مما قد يُحسّن صحة الخيول وأدائها بشكل كبير.

الكلمات المفتاحية: الذكاء الاصطناعي، التربية، الخيول، الصحة، الأداء.