Advantages of AI and ML over Other Doping Test Techniques

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***Abstract*— The involvement of artificial intelligence in the field of doping test represents a major advancement in combating some major performance, enhancing drug use in sports, unlike all the traditional methods that mostly depend on the complex chemical analysis and human interpretations, artificial intelligence. It provides a much more efficient and precise alternative way for detecting doping athletes, artificial intelligence systems process the huge amount of data collected from the athletes. Saliva blood in biological passports with the help of machine learning algorithms. And use them to detect the uncovered patterns and anomalies presence in the data. This finally results in a remote, more rapid and reliable identification of the doping cases, the continuous advancement of AI also allows the adaption of new doping strategies, which Helps in ensuring that the efforts made in anti-doping are ahead of any other emerging trends. Moreover, AI also helps in reducing the false positives and false negatives, encouraging data analysis precision and protecting the athletes from getting aimed at the earlier. Wrongful sanctions AI helps in improving the credibility of the testing procedures. Overall, it can be stated that AI provides a much adaptive approach and robust performance. It is a doping detection, thus, it also helps in contributing to a more fair decision-making process in the field of sports.**

I. INTRODUCTION

"Unequal chances, unfair competition, unclean sport – doping doesn't just violate the principle of fairness, sportsmen, and women who use performance-enhancing substances are putting their own health on the line." - Rory Shadbolt.

So, what exactly does doping imply? Intake of certain substances especially steroids is clearly banned for performers. This is because the intake of illegal substances is more often used to improve the performing ability and create a major hike in the strengths of the athletes. These types of banned drugs include stimulates and hormones that are injected in the player's body to increase efficiency. The exact level of prevalence of doping in elite sports and games is still unknown. According to research, World Athletics Championships claimed the prevalence to be somewhere between 15%. In this context, the World Anti-Doping Agency mentioned that laboratory tests sometimes are liable to give false results and cannot be trusted completely. Based on several anonymous questionnaires, the doping prevalence is said to vary between 39-62%. Hence, the introduction of artificial intelligence can be helpful in solving the doping test, providing a perfect way to eliminate the false results of Anti-doping tests from the roots. A massive amount of data is produced from several matches in sports. So, implementation of general statistical framework or biomedical laboratory tests fails to present expected outcomes.

II. OBJECTIVES

A. Review Stage

The primary objective of this research is the exploration and enhancement of the use of artificial intelligence in doping detection. It aims at integrating AI with the emerging technologies like blockchain variable devices, big data analytics and advanced imaging techniques. The goal is to address the major existing limitations in the traditional doping methods and development of a more accurate real-time detection system. The combination of AI with these technologies will finally seek to create a comprehensive and more reliable framework that will not only contribute in improving the detection accuracy, but also ensuring integrity of the data. Future doping trends can be easily analyzed and it will act as a supporting system for the sophisticated legal frameworks.

III. LITERATURE REVIEW

The existing body of literature underscores the increasingly significant role of artificial intelligence in the enhancement of doping detection methodologies, albeit persistent challenges continue to exist. Iljukov Schumacher (2017) accentuate the necessity for the establishment of standardized criteria within anti-doping performance profiling frame- works. Elbe Brand (2014) elaborate on the behavioral impediments encountered, such as difficulties with urination during doping control assessments. WebMD (2023) delineates the health risks associated with blood doping alongside the challenges inherent in its detection, while emerging methodologies like Dried Blood Spot testing necessitate further empirical validation (Sport Integrity, 2022). The potential of artificial intelligence is highlighted, with research indicating its efficacy in identifying subtle patterns (Uni Saarland, 2022) and in the context of blood doping (ISS, 2022), although limitations related to data quality and the integration of complementary techniques remain critical for progress (DFKI, 2024; PubMed, 2024).

IV. RESEARCH GAP

Within the extant literature, numerous investigations have delved into the implementation of artificial intelligence and machine learning in the realm of doping detection; however, significant gaps persist that hinder their practical applicability and broader acceptance. For example, Pomi and G´orski (2019) illustrated the potential of machine learning in identifying erythropoiesis-stimulating agents, yet their analysis was constrained by a limited dataset and failed to address the model's generalizability to various doping substances.

In a similar way, Robinson et al. (2011) emphasized the impact of the Athlete Biological Passport (ABP) that helps in longitudinal monitoring. He also acknowledged that the mentioned method for doping test is very frequent in encountering difficulties with false positives. Additionally, another research by Pavlidis et al. (2020) successfully scrutinized complex biomarker data with the implementation of deep learning procedures. Though it was found to encounter several issues which contradicted the model's decision and hence, making it complicates to adopt such methods. Clear understanding regarding the underlying data was not evident which restricted the anti-doping organizations to adopt such techniques. Due to these identified limitations and challenges, AI/ML models emerged out to be one of the most convenient one in regards of simplicity as well as providing high accuracy. Yet, concerns need to be put to the model interpretability, model validity, model generalizability, and data heterogeneity. This research is concerned in analyzing several aspects of doping test and comparison of various methods in addressing those techniques with the help of visualizations. It will clearly depict the reliability and advantages of AI and M techniques in doping test thereby making this technique more optimal for acceptance.

V. METHODOLOGY

A. Research Approach

Inevitably, groundbreaking opportunities have been provided by the implementation of Artificial Intelligence and Machine Learning which significantly showed its higher ability to provide better accuracy, efficiency, and reliability when made comparison with traditional testing techniques. This survey paper is aimed at analyzing several methodologies applies for the research work with the help of the data collected from multiple sources.

Primarily, the research begins with an overview that helped in describing the traditional techniques used for doping test. These traditional techniques included gas chromatography-mass spectrometry, liquid chromatography-mass spectrometry and many more. Though these techniques depicted highly accurate results, yet due to certain limitations they can create problems in finding the accurate output. In this regard, AI and ML are ready to address the problems which are lagged by the traditional techniques.

B. Data Sources

The primary data source includes the World Anti-Doping Agency (WADA) database World Anti-Doping Agency (2021). The data collected helps in creating an excel sheet which includes columns such as their accuracy, time required, sample needed, sensitivity, and specificity etc. The excel sheet was then exported to Tableau and visualizations were conducted which clearly depicted the efficiency of AI and ML in every aspect.

C. Evaluation Criteria

The evaluation of the fact whether AI and ML serves as the most optimum technique for the doping test in athletes not only depends on the accuracy of the technique. It also depends on the other factors influencing the test technique. Hence, concentrating only on accuracy might be misleading. Precision plays a very significant role in detecting the true positive factors. On the other hand, recall helps in establishing the ability of the model. All the factors contributing to the evaluation metrics are equally crucial for determining the validity of the model. Hence, it is utterly necessary that the evaluation metric for AI and ML models in doping detection is designed very carefully.

D. Comparison Framework

A comparison framework ensures conducting a head-to-head comparison between AI/ML techniques and the traditional techniques of doping techniques in several aspects such as specificity, time needed to process the data and produce the output, sensitivity, and ability to handle a large dataset Sottas et al. (2006). Hence, both technical performance and practical implications are needed to be considered by the comparison framework.

E. Tools and Techniques

"At the moment, the samples are all analyzed manually", - Wolfgang Maaß, Professor of Information Systems for the Service Industry at Saarland University and Scientific Director of the Smart Service Engineering research department at the German Research Center for Artificial Intelligence (DFKI)." The most reliable method till date was DNA test which included lots of expense and time. But the use of AI algorithms is effective in analyzing the suspicion in athletes that might have occurred due to doping. Age, body weight, performance level are considered to detect anomalies and the presence of unexpected outputs. In some cases, urine samples might be taken but this method demands very less amount of urine and does not affect the players' health unlike traditional methods of urine test.

VI. DISCUSSION AND RESULTS

A. Doping Detection and Traditional Techniques

The doping detection in sports arena has always shown its dependency on methods such as Enzyme-Linked Immunosorbent Assay (ELISA) and Gas Chromatography- Mass Spectrometry (GC-MS), which besides being efficient, are limited by the need for prior knowledge regarding some significant substances. They also were proven to be vulnerable to the appearance of incorrect outputs Dupont et al. (2024). With the evolvement of doping techniques over time, it started encompassing approaches like gene doping and microdosing. These conventional methods showcased several limitations in their efficiency. The quality of its implications and financial requirements associated with the advanced technologies such as artificial intelligence and machine learning have grown an exclusive interest in their increased usage. These techniques are proven to be more holistic and have extensive adaptive framework for the recognition of doping practices.

B. Usefulness of AI in Doping Detection

Artificial Intelligence and Machine Learning underwent various improvement processes in making the field of sports completely anti-doping. Specialized scrutinization were conducted to make AI better every day. The scrutinization ultimately helped in increasing the overall efficacy and accuracy of the AI formulated models. Additionally, AI and ML models also provided information about non-biological data which included performance metrics and interaction on social media. As a result, it became easy to create comprehensive profiles of athletes, hence helping in the recognition of anomalies associated with the doping behaviors. Moreover, the contribution of AI-generated models in providing trends, patterns and a wide range of future possibilities assisted in creating proactive strategies in the fight against doping practices.

C. Health Issues Related to Traditional doping Detection Techniques

There are three major doping test techniques which are currently in use in the sports arena which includes urine, venous blood and dried blood spot. Athletes are highly liable to suffer from urination difficulties while going through the urine test technique of doping tests Elbe et al. (2014). Players suffering from maximum urination trouble during doping tests are more likely to have low levels of oppositional behavior. Athletes use blood transfusions to enhance their performance ability through doping. This culminates in an elevated likelihood of bloodborne infections, human immunodeficiency virus (HIV) transmission, hepatitis infection, hyperkalemia, hypertension, and bacterial infections Jelkmann, W. (2016). Athletes are also prone to suffer from acute lung injury and at a high risk of getting strokes and heart attacks. Use of dried blood spots is another technique to test the doping level in athletes. It constitutes an expedited and more straightforward methodology for assessing the existence of pharmacological substances within the human organism. But there remains a chance that a severe disease known as Purpura can cause life risk by clotting the blood and lowering the platelet levels Cleveland Clinic. (2021, August 26). Use of the traditional testing procedures involve collecting samples repeatedly in case the test needs to be conducted multiple times. Modeling in AI can run the code multiple times with the same sample. Due to the increasing risk of health problems associated with these traditional doping methods, the latest technique of doping test can be put into action which involves the AI for the testing procedure making it more fruitful and less risky.

D. Case Studies and Real-World Applications of AI in Doping Detection

The application of AI in doping detection has been tested and validated through several case studies, showcasing its potential to enhance the accuracy and efficiency of traditional methods. Here are some notable examples:

(I) Athlete Biological Passport (ABP) Analysis with AI

The Athlete Biological Passport (ABP) involves a method which was developed by the World Anti-Doping Agency (WADA). This tool helps in monitoring the biological variables in a systematic order. Hence, it indirectly facilitates the recognition of effects caused by doping in athletes. A path-breaking case study was conducted by WADA in their laboratory situated in Switzerland. The researchers used machine learning techniques to increase the analytical ability of Athlete Biological Passport (ABP) data Zorzoli, M. (2011). Conventional techniques primarily were found to strengthen their finding based on statistical methodologies to distinguish the deviation from grounded standard values, though it frequently overlooked the underlying false positive values. The laboratory in Switzerland acquired AI models which were trained on global datasets of ABP. This was useful in detecting anomalies that lined up with doping activities. The implementation of AI techniques significantly improved the doping detection by involving individual variations. On the other hand, the AI and ML model also subsequently reduced the occurrence of false positives and false negatives. The establishment of artificial intelligence in the arena of doping detection increased the specificity of the testing remarkably. The outputs provided were more accurate and more reliable as it also addressed other variables affecting the accuracy. This researched highlighted the effective potential of AI in doping detection and as a consequent enhanced its wider usage within WADA-recognized laboratories.

(II) Detection of Erythropoietin (EPO) Doping Using AI

Erythropoietin (EPO) is a hormone that enhances the increment of the synthesis of red blood cells and also have the ability to work for the betterment of endurance performance. The segmentation of synthetic EPO from its endogenous counterpart involves distinguishable issues due to their similarities in structure. Researchers at the University of Lausanne have coined an AI based model which possess the ability to discriminate between natural and synthetic EPO in blood samples. Traditional methodologies demanded the use of huge, intricate samples and they could be characterized with the help of prolonged analysis time. The AI model was based on several machine learning algorithms which were found to be providing proficient outputs even for smaller volume of blood specimen. Since, the model was properly trained both with natural and synthetic EPO, hence, it incorporated the ability to showcase classification of novel samples with improved accuracy John et al. (2012). Extensive sensitivity as well as specificity was exhibited by the newly formed AI model when compared to the traditional methods. The AI and ML model was highly successful in identifying synthetic EPO even in conditions where standard testing techniques might perform inadequately. This research illustrates the possible abilities of artificial intelligence to improve EPO detection techniques, thereby furnishing them to be more useful and precise. It also supports further wider range of applications of AI innovations and technologies in fighting against blood doping.

(III) AI-Based Steroid Detection in Urine Samples

The presence of some substances in anabolic steroids influences the performance of athletes. Identification of such substances in athletes is essential to maintain the fairness of the game. The presence of metabolites in urine specimen are checked with the help of some predominant traditional techniques such as mass spectrometry. But this process proves out to be extremely laborious and demands expert consideration Smith et al. (2023). Several researchers came together and put their efforts in formulating a model based on the algorithms of artificial intelligence to improvise the steroid detection in urine specimens. The research aimed at addressing the challenges which were associated with the identification of novel steroids. The study also ensured higher precision in spite of the existence of complicated metabolite profiles. Mass spectrometry data were used to train the AI and ML model. The data were derived from several urine samples which have been subjected to steroid testing. The model was such created which would spot the patterns that suggests steroid usage involving substances that are similar yet not exact identical to recognized steroids. The proficiency of the artificial intelligence model was extremely noteworthy and reliable in recognizing both conventional and innovative designer steroids. It put a major impact in reducing the duration of analysis and helping doping control agencies that are operable under stringent time limits. This methodology elaborated the extreme potential of artificial intelligence in detecting a wide spectrum of steroids. Hence, such technique can prevent the athletes from using modified substances.

E. Challenges/Limitations

The implementation of AI in the field of doping detection faces various challenges which also includes scarcity and probable bias involved in the existing data. Hence, there is a constant concern required to maintain the privacy and ethics of the necessary datasets. The dynamic evolution of doping methodologies necessitates the ongoing adaptation of artificial intelligence systems. Ethical considerations, particularly pertaining to privacy and informed consent, are equally significant. Furthermore, the incorporation of artificial intelligence into pre-existing frameworks necessitates technical enhancements, specialized knowledge, and substantial investments in both infrastructure and training to guarantee effective execution.

F. Integration of AI with Other Technologies

Integration of Artificial Intelligence with other emerging technologies will definitely in- crease its effectiveness to the next level. Blockchain can effortlessly secure and offer assistance in confirming the information given by a competitor, making it tamper-proof additionally expanding the reliability of the comes about that's created by the AI and ML calculations. Some other wearable technologies such as fitness trackers also help in providing and monitoring the physiological parameters of athletes which allow AI to detect the sudden changes that might occur due to the intake of doping during an ongoing sport University of Saarland. (2022). The combination of Artificial Intelligence with big data analytics will help in identifying the emerging doping trends and patterns that are collected by analyzing the data from multiple sources. Moreover, when paired with advanced imaging techniques such as MRI and PET scans, then AI will offer a non-invasive detection of doping with maximum accuracy Manfredini et al. (2011). Such integrations also help in the development of sophisticated legal frameworks for detecting doping in athletes.

G. Visualizations

Data has been collected based on several research papers, survey papers, and journals to understand the sensitivity, specificity, cost, accuracy, samples required, time needed by each doping test technique to draw the results. Based on these data certain visualizations have been created using Tableau to compare each of the techniques.

Visualization 1

A horizontal bar diagram is constructed for the visualization of accuracy of several techniques used for doping tests and also the type of sample needed for the test is visible. The visualization clearly depicts the highest accuracy to be achieved by AI and ML Techniques with an accuracy of almost 97%.

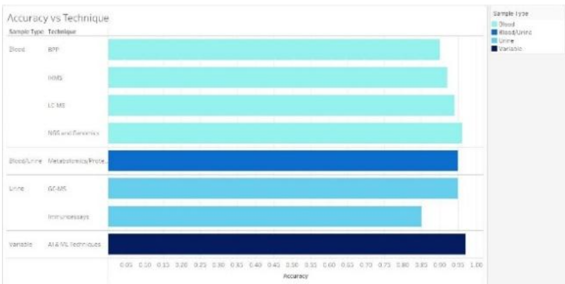

Fig.1: Accuracy vs Technique

From the diagram, it is clearly evident that techniques like BPP, IRMS, LC-MS, NGS and Genomics strictly require blood samples for the detection of doping in athletes. Whereas, GC-MS and Immunoassays require urine for the test. Only Metabolomics can conduct the test be it blood or be it urine. But, most significantly AI and ML Technique can fetch almost accurate results with variable samples that includes blood, urine, saliva etc.

Visualization 2

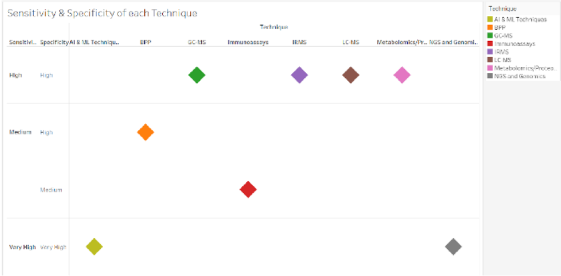

Fig.2: Comparison of sensitivity and specificity of each technique

A scatter plot is constructed for the visualization of sensitivity and specificity of each technique used for doping tests. The visualization clearly depicts that AI and ML Technique has the highest specificity among all the other techniques. Though having highest sensitivity might create some problems in the procedure of testing.

Visualization 3

Fig.3: Comparison of cost and time required for each technique

A scatter plot is constructed for the visualization of sensitivity and specificity of each technique used for doping tests. The visualization clearly shows that AI and ML Technique requires medium cost to complete the whole testing procedure. Too, modeling of huge datasets can be exhausted real-time.

H. Advantages of AI Over Traditional Techniques

There are several advantages of using AI over other techniques of doping tests DFKI (2024). They are as follows:

Cost Management: Automation of the analysis process reduces the need of manual labor which ultimately reduces the budget of the procedure. Once the modeling is done, and the automation is complete, AI systems are able to process a huge set of data very rapidly with no further cost or investment.

Accuracy: AI algorithms are seen to produce highly accurate data compared to other doping test techniques.

Specificity: AI and ML techniques in doping tests come with very high precision which reduces the presence of false positive and false negative results.

Time Efficiency: It takes some time to formulate the model but once the model is prepared it detects the data very rapidly. This contributes a lot in faster decision-making when some doping cases come up in the middle of any ongoing sports. Overall, AI streamlines the detection process, making it more cost-effective, accurate, specific, and efficient.

I. Comparison with Other Emerging Technologies

The basic advantage of Artificial Intelligence in the field of doping tests is that it stands out for its accuracy, specificity, detection timing, and cost management. The gradually emerging technologies such as Next Generation Sequencing (NGS) and Metabolic provide a detailed insight about the biological aspects of the dataset. These are most of the time very much expensive and time-consuming University of Saarland. (2022). Artificial intelligence, on the contrary, helps in quickly identifying the patterns and the outliers present in the data with the help of modeling and AI algorithms. The cost is also reduced along with enhanced accuracy. A few other strategies such as isotope proportion mass spectrometry (IRMS) regularly give higher specificity but are less versatile than AI Kelly et al. (2019). The ability of AI to understand and adapt to new methods of doping techniques further makes it more eligible and superior for the analysis of real-time data analysis and efficiency in detection

VII. CONCLUSION

Artificial Intelligence has proven its breakthrough achievement in the field of doping tests over other traditional testing methods Dupont et al. (2024). The automation of data analysis reduces the fault positives and helps in adaptation of new doping strategies, which rapidly and effectively works when compared to other emerging technologies. Future inquiries about ought to center on coordination AI with other progressed strategies, such as NGS and metabolomics, to improve multi-faceted discovery capabilities Galily, Y. (2018). It should also focus on the integration of AI with other advanced techniques so that the multifaceted detection capabilities are enriched to another extent. The exploration of AI's role in the prediction of emerging doping methods and improvement of its adaptability through continuous learning will definitely help in future studies and prove to be crucial in real life. Moreover, exploring cost effective ways to convey AI on a bigger scale in anti-doping endeavors may advance its affect. AI definitely represents a very significant advancement in doping detection by offering a blend of precision and efficacy that enriches the integrity of sports and real-time data analysis DFKI (2024). Continued innovation and further researches will stabilize AI's role in maintaining a fair gameplay and help in reducing doping effectively in sports arena.

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