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Editorial

Expanding the Frontiers of Data Science Across Diverse Disciplines

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Abstract

The omnipresence of data in today's world necessitates innovative approaches to its analysis and application across diverse scientific fields. This editorial for the International Journal of Data Science (IJDS) outlines the journal's vision, emphasizing interdisciplinary research in Agricultural Data Science, Health Sciences Data Science, Life Sciences Data Science, Forensic Sciences Data Science, and General Data Science. Each section showcases how data science transforms traditional disciplines, offering insights and solutions to complex challenges. In Agricultural Data Science, precision agriculture, crop yield prediction models, and climate impact assessments are highlighted, showcasing the use of big data and AI to optimize resource management and enhance sustainable practices. Health Sciences Data Science focuses on predictive models for disease progression, AI in diagnostic imaging, and integrating electronic health records with genomics to advance personalized medicine and healthcare delivery. Life Sciences Data Science delves into genomic data analysis, proteomics, and systems biology, emphasizing the role of data science in understanding biological processes and ecosystems. It also explores the use of machine learning (ML) for evolutionary pattern recognition and ecological forecasting. Forensic Sciences Data Science underscores advancements in digital forensics, pattern recognition, and data integration methodologies, enhancing the accuracy and efficiency of crime scene analysis and legal investigations. The section on General Data Science covers innovative algorithm development, ML advancements, and critical reviews of data science education and ethical practices. This foundational knowledge underpins the specialized applications discussed in other sections, promoting a comprehensive understanding of data science principles and their universal relevance. The IJDS aims to bridge the gap between traditional disciplines and modern data science, fostering research collaborations and disseminating knowledge that addresses both specialized and general interests. By inviting researchers, practitioners, and educators to contribute, the journal ensures that data science is harnessed ethically and effectively across all scientific domains. This editorial reflects the IJDS's commitment to driving innovation, promoting ethical practices, and advancing the field of data science to tackle the complex challenges of our time. Through rigorous research and interdisciplinary collaboration, the IJDS aspires to be a catalyst for change and a forum for groundbreaking discoveries in data science.

Keywords: Data Science, Machine Learning, Artificial Intelligence, Interdisciplinary Research, Precision Agriculture, Health Data Analytics, Forensic Data Science, Genomic Analysis.

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1. Introduction

The omnipresence of data in the modern world necessitates innovative approaches to its analysis, interpretation, and application. As the field of Data Science continues to evolve, its integration into various domains not only enriches these fields but also expands the scope and capability of data-driven decision-making (Figure 1).

Data Science's impact is evident in numerous fields. For instance, in the agricultural sector, data-driven approaches are being utilized to enhance crop yields, optimize resource usage, and predict climate impacts, leading to more sustainable farming practices (Kamilaris et al., 2018). In health sciences, the application of big data and ML algorithms (Figure 2) has significantly improved disease diagnosis, treatment personalization, and patient care (Shilo et al., 2020). Life sciences benefit from data science through advancements in genomic analysis, which enable researchers to uncover complex biological processes and evolutionary patterns (Marx, 2013). Forensic science, too, has seen transformative changes with data analytics improving the accuracy of crime scene investigations and legal proceedings (Casey, 2011).

The IJDS is committed to exploring and disseminating research at the intersection of data science and these diverse fields (Figures 1 and 2). This editorial outlines the vision for the upcoming issues of IJDS, emphasizing interdisciplinary research and collaboration across fields such as Agricultural Data Science, Health Sciences Data Science, Life Sciences Data Science, Forensic Sciences Data Science, and General Data Science. By fostering a platform for comprehensive research, innovative methodologies, and critical analysis, IJDS aims to contribute significantly to the advancement of Data Science and its applications in solving real-world problems.

2. Agricultural Data Science

The urgency of addressing global food security and sustainable agricultural practices has never been greater. With the global population projected to reach 9.7 billion by 2050, ensuring adequate food supply while preserving environmental resources poses a significant challenge (FAO, 2017). Agricultural Data Science emerges as a critical field in addressing these issues by leveraging Data Analytics, ML, and Big Data to revolutionize traditional farming practices (Figure 2).

Precision Agriculture, a key component of Agricultural Data Science, involves the use of technologies such as GPS, remote sensing, and Internet of Things (IoT) devices to collect real-time data on crop conditions, soil health, and weather patterns (Figure 2). This data-driven approach enables farmers to make informed decisions about planting, irrigation, fertilization, and pest control, ultimately increasing productivity and resource efficiency (Zhang et al., 2019). For instance, variable rate technology (VRT) allows for the precise application of inputs like water and fertilizers based on the specific needs of different areas within a field, reducing waste and environmental impact (Mulla, 2013).

Crop yield prediction models, another vital aspect, utilize historical data, weather forecasts, and satellite imagery to forecast crop production. These models help farmers and policymakers make better decisions regarding crop planning, market supply, and food distribution (Lobell et al., 2015). For example, ML algorithms can analyze diverse datasets to predict the impact of various factors on crop yields, enabling proactive measures to mitigate risks associated with climate change and extreme weather events (Abrahart and See, 2000; Schlenker and Roberts, 2009).

Climate impact assessments are essential in understanding how changing climate conditions affect agricultural productivity and sustainability. By integrating climate data with crop models, researchers can simulate different scenarios and develop strategies to adapt to and mitigate climate change effects on agriculture (Abrahart and See, 2000; Schlenker and Roberts, 2009). This includes identifying crop varieties resilient to drought, heat, and pests, thereby enhancing food security in vulnerable regions (Webber et al., 2014; Raza et al., 2019).

Upcoming publications in IJDS will focus on the use of big data and AI to optimize resource management, enhance pest and disease prediction, and innovate bioengineering. For instance, big data analytics can track pest outbreaks and predict future occurrences based on weather patterns and crop conditions, allowing for timely and targeted interventions (Westbrook et al., 2016). Bioengineering innovations, such as genetically modified crops, can further boost agricultural productivity and resilience, addressing both food security and environmental sustainability (Huang et al., 2002).

Moreover, this area will explore the socio-economic impacts of data-driven agriculture on rural communities. The adoption of advanced technologies in agriculture can improve livelihoods by increasing farm incomes and reducing labor-intensive tasks.

Figure 1. Intersection between AI, ML, and Data Science.

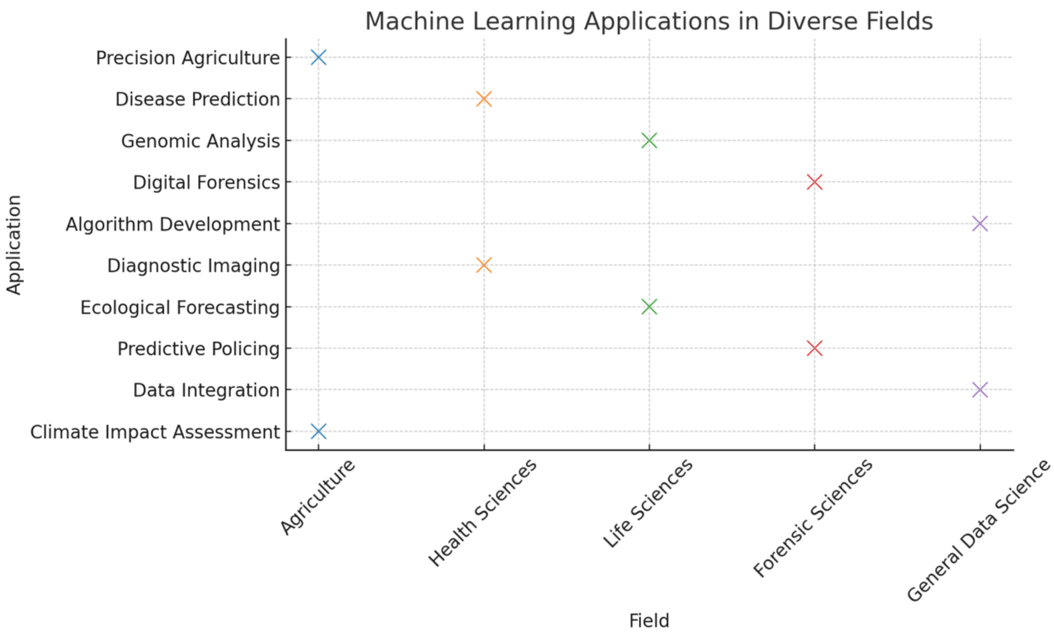

Figure 2. ML applications in diverse fields.

However, it also raises concerns about digital divide and equitable access to technology among smallholder farmers (Foley et al., 2011). Research will address these challenges, proposing solutions to ensure inclusive and sustainable agricultural development.

3. Health Sciences Data Sciencess

Health Sciences Data Science has revolutionized medical research, diagnostics, and treatment paradigms. The potential to leverage vast amounts of medical data can lead to breakthroughs in personalized medicine and epidemiology (Figure 2). Future articles will delve into the development of predictive models for disease progression, AI in diagnostic imaging, and the ethical implications of data usage in medicine. Special attention will be dedicated to integrating electronic health records with genomics and biometrics to foster innovations in healthcare delivery.

3.1. Revolutionizing Medical Research and Diagnostics

The integration of Data Science into medical research has enabled the analysis of large datasets, including genomic, proteomic, and clinical data, facilitating the discovery of new biomarkers and therapeutic targets (Hood and Flores, 2012) (Figure 2). Predictive models for disease progression, developed through ML algorithms, can analyze patient data to predict the likelihood of disease onset, progression, and response to treatment (Obermeyer and Emanuel, 2016). These models are particularly valuable in managing chronic diseases such as diabetes, cardiovascular diseases, and cancer, where early intervention can significantly alter disease trajectories (Topol, 2019).

AI in diagnostic imaging represents another transformative application. ML algorithms can enhance the accuracy of image interpretation in radiology, pathology, and dermatology, reducing diagnostic errors and improving efficiency (Figures 1–4) (Litjens et al., 2017). For example, convolutional neural networks (CNNs) have demonstrated high accuracy in detecting abnormalities in medical images, such as tumors in mammograms and lesions in CT scans (Esteva et al., 2017). These advancements not only assist clinicians in making more informed decisions but also enable the development of automated diagnostic tools for resource-limited settings.

3.2. Personalized Medicine and Integrative Health Data

Personalized medicine aims to tailor medical treatment to individual characteristics, such as genetic profile, lifestyle, and environment. By integrating electronic health records (EHRs) with genomic and biometric data, healthcare providers can offer more precise and effective treatments (Collins and Varmus, 2015). For instance, pharmacogenomics, the study of how genes affect a person's response to drugs, can guide the selection of medications that are most likely to be effective and cause fewer side effects (Figures 1–4) (Roden et al., 2011).

Integrative health data platforms that combine EHRs with other data sources, such as wearable devices and mobile health applications, enable continuous monitoring of patients' health status. This holistic view facilitates proactive health management, early detection of potential health issues, and personalized intervention strategies (Wang et al., 2018). The ability to analyze real-time data from various sources can lead to more dynamic and adaptive healthcare systems.

3.3. Ethical Implications and Data Privacy

As the use of data in healthcare expands, so do concerns about data privacy, security, and ethical implications. The col-

Figure 3. Data Science process and tools.

lection, storage, and analysis of sensitive health information must adhere to strict ethical guidelines and regulatory standards to protect patient privacy (Safran et al., 2007). Future articles in IJDS will explore these challenges, discussing frameworks for ensuring data security and ethical use of health data. Topics such as informed consent, data anonymization, and the balance between data utility and privacy will be critically examined.

Moreover, the potential for algorithmic bias in AI-driven healthcare applications must be addressed. Ensuring that predictive models and diagnostic tools are trained on diverse datasets representative of various populations is crucial to avoid disparities in healthcare outcomes (Obermeyer et al., 2019). Research focusing on the fairness and transparency of AI in healthcare will be prioritized to promote equitable healthcare access and delivery.

3.4. Innovations in Healthcare Delivery

Innovative healthcare delivery models driven by data science are reshaping the patient care landscape. Telemedicine, supported by data analytics, has become increasingly important, especially in the wake of the COVID-19 pandemic, enabling remote diagnosis, consultation, and treatment (Keesara et al., 2020). Predictive analytics can optimize hospital resource allocation, reduce patient wait times, and improve overall operational efficiency (Froehle and White, 2014).

Additionally, predictive maintenance of medical equipment, powered by IoT and data analytics, ensures that critical devices are operational and reduces downtime, thereby enhancing the quality of patient care (Hermes et al., 2020). The integration of AI-driven chatbots and virtual health assistants into healthcare systems also provides patients with instant access to medical information and support, improving patient engagement and adherence to treatment plans (Figures 1–4) (Bickmore et al., 2018).

4. Life Sciences Data Science

In Life Sciences, data science offers profound insights into biological processes and ecosystems' complexities. The forthcoming content aims to cover bioinformatics, genomic data analysis, proteomics, and systems biology. Contributions will also include studies on biodiversity conservation using drone and satellite imagery, ML models for understanding evolutionary patterns, and computational strategies for ecological forecasting (Figures 1–4).

4.1 Genomic Data Analysis

Genomic data analysis is at the forefront of life sciences, providing critical insights into the genetic underpinnings of various organisms. The sequencing of genomes generates massive datasets that require sophisticated computational tools for analysis. Data science techniques, such as ML and artificial intelligence, are essential for interpreting these complex datasets. They enable researchers to identify genetic variants associated with diseases, understand genetic diversity, and develop personalized medicine approaches (Deisboeck and Zhang, 2011). For instance, quantitative trait loci (QTL) mapping and genome-wide association studies (GWAS) have leveraged data science to pinpoint genes linked to complex traits and diseases (Visscher et al., 2017).

4.2. Proteomics

Proteomics, the large-scale study of proteins, their structures, and functions, generates extensive datasets that are critical for understanding cellular processes. Data science and bioinformatics tools facilitate the analysis of proteomic data, allowing for the identification of protein interactions, pathways, and functions (Aebersold and Mann, 2016). ML algorithms can predict protein structures and functions from sequence data, aiding in the discovery of new drug targets and biomarkers. Additionally, integrative approaches combining proteomic and genomic data provide a holistic view of biological systems, enhancing our understanding of disease mechanisms (Wilhelm et al., 2014).

4.3. Systems Biology

Systems biology aims to understand the complex interactions within biological systems, integrating data from genomics, proteomics, metabolomics, and other omics fields. Data science and bioinformatics methodologies are crucial in modeling these interactions and predicting system behaviors. For example, network analysis can reveal key regulatory pathways and interactions that control cellular functions (Kitano, 2002). Computational models can simulate biological processes, providing insights into how genetic and environmental factors influence health and disease (Karr et al., 2012).

4.4 Biodiversity Conservation

The application of data science in biodiversity conservation is transforming how we monitor and protect ecosystems. Remote sensing technologies, such as drones and satellite imagery, generate large datasets that can be analyzed to track changes in land use, habitat fragmentation, and species distributions (Pettorelli et al., 2014). ML models can predict species distribution patterns and identify critical habitats for conservation efforts.

These technologies enable real-time monitoring of ecosystems, allowing for timely interventions to protect endangered species and manage natural resources sustainably (Turner et al., 2015).

4.5. Evolutionary Patterns and Ecological Forecasting

Understanding evolutionary patterns is crucial for unraveling the history of life on Earth. Data science and bioinformatics approaches, such as phylogenetic analysis and evolutionary modeling, provide insights into the evolutionary relationships among species and the mechanisms driving evolution (Yang and Rannala, 2012). ML models can analyze genetic data to infer evolutionary histories and predict future evolutionary trends.

Ecological forecasting uses computational strategies to predict future changes in ecosystems due to factors such as climate change, habitat loss, and species invasions (Clark et al., 2001). These models can simulate different scenarios, helping policymakers and conservationists develop strategies to mitigate adverse effects on biodiversity and ecosystem services.

5. Forensic Sciences Data Science

Data science in Forensic Sciences provides powerful tools for crime scene analysis and legal investigations. Emphasizing advancements in digital forensics, upcoming issues will feature research on data analytics for improving the accuracy and efficiency of forensic testing, the use of AI for pattern recognition in forensic evidence, and the development of new methodologies for data integration in forensic cases (Figures 1–4). This section of the IJDS will highlight cutting-edge research and developments in digital forensics, pattern recognition, and data integration methodologies that are transforming forensic science.

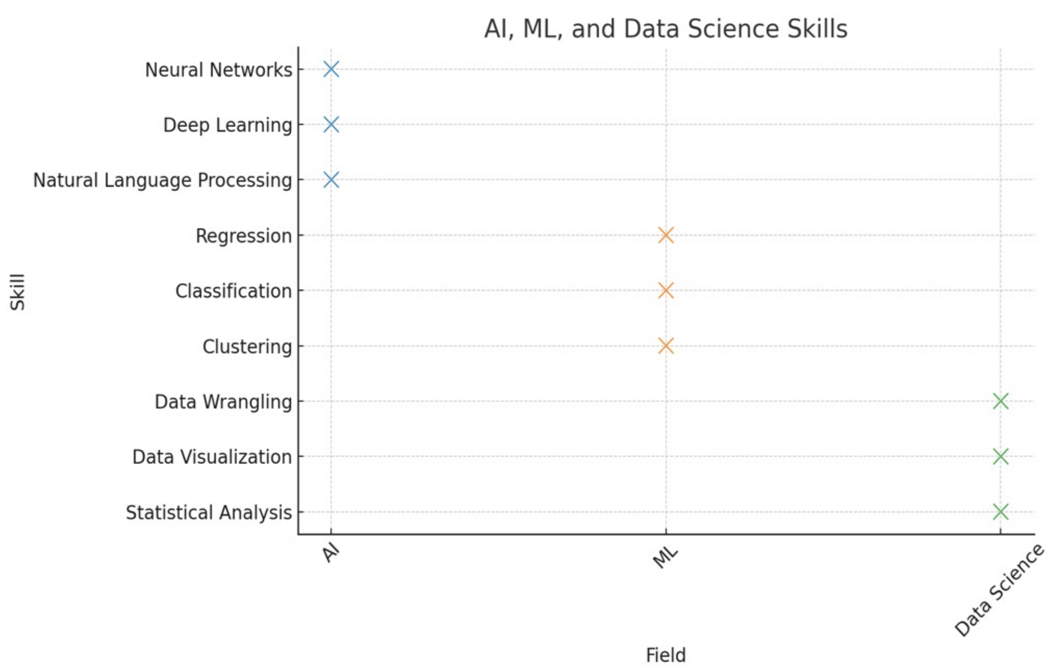

Figure 4. AI, ML, and Data Science skills.

5.1. Advancements in Digital Forensics

Digital forensics involves the recovery and investigation of material found in digital devices, often in relation to computer crimes. As technology advances, the volume and complexity of digital evidence increase, requiring sophisticated data science techniques to manage and analyze this information effectively. Data analytics can sift through vast amounts of data to identify relevant patterns and anomalies that might be critical in an investigation (Casey, 2011).

ML algorithms are particularly useful in digital forensics for tasks such as identifying malicious software, detecting fraud, and analyzing network traffic to uncover illicit activities (Beebe, 2009). For instance, anomaly detection algorithms can flag unusual patterns in data that may indicate cyber intrusions or data breaches (Chandola et al., 2009). Additionally, AI can automate the tedious process of sorting through large datasets, significantly speeding up investigations and reducing the potential for human error.

5.2. Pattern Recognition in Forensic Evidence

AI and ML are making significant strides in pattern recognition, a crucial aspect of forensic science. These technologies can analyze forensic evidence such as fingerprints, DNA, and ballistic markings with a high degree of accuracy, surpassing traditional methods in both speed and precision (Galante and Li, 2023). For example, deep learning algorithms can be trained to recognize patterns in complex data, such as DNA sequences, which can then be used to match samples with a high level of confidence (Richmond et al., 2021).

In fingerprint analysis, AI systems can compare prints with vast databases to find matches, improving the efficiency and accuracy of the identification process (Jain and Feng, 2011). Similarly, in ballistic forensics, ML models can analyze markings on bullets and cartridge cases to link them to specific firearms, aiding in criminal investigations (Tai et al., 2014).

5.3. New Methodologies for Data Integration in Forensic Cases

Forensic science often requires the integration of diverse data sources, including physical evidence, digital data, and witness testimonies. Developing methodologies for seamless data integration is essential for building comprehensive forensic models that can provide a holistic view of a case. Data science plays a crucial role in creating frameworks and algorithms that can merge these varied datasets, ensuring that all relevant information is considered in an investigation (Stolfo et al., 2000).

One emerging area is the use of graph databases to model relationships between different pieces of evidence. These databases can visualize connections and patterns that might not be apparent through traditional analysis, helping investigators to piece together complex cases (Angles and Gutierrez, 2008). Additionally, the use of blockchain technology for maintaining the integrity of forensic data is gaining traction. Blockchain's immutable ledger ensures that evidence remains tamper-proof and that the chain of custody is transparently documented (Kumar et al., 2018).

5.4 Ethical and Legal Implications

As data science techniques become more embedded in forensic science, ethical and legal considerations must be addressed. The use of AI and ML in forensics raises questions about the potential for bias, the transparency of algorithms, and the admissibility of AI-generated evidence in court (Geradts, 2018). Ensuring that forensic tools are developed and deployed in a manner that respects individuals' rights and maintains public trust is paramount.

Future issues of IJDS will explore these ethical and legal challenges, providing guidelines and best practices for the responsible use of data science in forensic investigations. Topics such as the validation of forensic algorithms, the standardization of digital evidence procedures, and the implications of AI-driven decisions in the justice system will be critically examined.

6. General Data Science

General Data Science remains a cornerstone of this journal, reflecting on methodologies, theories, and tools that underpin specific applications in other fields. Articles will include innovative algorithm development, advances in ML techniques, and critical reviews of data science education and ethical practices. This section aims to foster a deeper understanding of data science's fundamental principles and their universal applications.

6.1. Innovative Algorithm Development

The development of new algorithms is at the heart of data science, driving progress across various applications. Researchers are continually seeking ways to enhance algorithmic efficiency, accuracy, and scalability. Innovations in this area include the creation of algorithms that can process vast datasets more quickly and accurately, as well as those that can handle the increasing complexity of data types and sources. For example, the development of deep learning algorithms has revolutionized areas such as image recognition, natural language processing (NLP), and predictive analytics (LeCun et al., 2015).

One significant advancement is the development of reinforcement learning algorithms, which enable systems to learn and adapt based on interactions with their environment. These algorithms have been successfully applied in diverse areas, from robotics to finance (Sutton and Barto, 2018). Moreover, the emergence of quantum computing promises to further revolutionize algorithm development by enabling the processing of complex computations that are currently infeasible with classical computers (Montanaro, 2016).

6.2. Advances in ML Techniques

ML is a core component of data science, and advances in ML techniques continue to push the boundaries of what is possible. Researchers are developing new models and improving existing ones to enhance their performance and applicability. For instance, transfer learning techniques allow models to leverage knowledge from one domain to improve performance in another, reducing the need for large amounts of labeled data (Pan and Yang, 2010). Similarly, generative adversarial networks (GANs) have shown remarkable capabilities in generating realistic synthetic data, which can be used for training other models (Goodfellow et al., 2014).

Another significant area of advancement is the development of explainable AI (XAI) techniques. As ML models become more complex, understanding and interpreting their decisions becomes increasingly challenging. XAI aims to make these models more transparent, providing insights into how they make decisions and thereby increasing trust and accountability in AI systems (Doshi-Velez and Kim, 2017).

6.3. Critical Reviews of Data Science Education

The rapid growth of data science as a field has led to a corresponding increase in educational programs designed to train the next generation of data scientists. However, there is a need for critical reviews of these educational efforts to ensure they meet industry needs and academic standards. Articles in this area will examine the current state of data science education, identifying best practices, challenges, and opportunities for improvement. For example, curriculum development is a key focus, with an emphasis on balancing theoretical knowledge and practical skills. The integration of interdisciplinary approaches, combining elements of computer science, statistics, and domain-specific knowledge, is essential for preparing students to tackle real-world problems (Baumer, 2015). Additionally, the importance of experiential learning, through internships, projects, and collaborations with industry, will be highlighted as a critical component of effective data science education (Hardin et al., 2015).

6.4. Ethical Practices in Data Science

As data science becomes increasingly integrated into various aspects of society, ethical considerations are paramount. Articles in this section will address the ethical challenges associated with data collection, analysis, and application. Topics will include data privacy, bias in AI algorithms, and the responsible use of data.

One critical area of concern is the potential for bias in AI systems. Bias can arise from various sources, including biased training data, flawed model assumptions, and human biases in algorithm design. Addressing these issues requires a multifaceted approach, including the development of fair and unbiased algorithms, transparent reporting of model performance, and ongoing monitoring and evaluation (Barocas et al., 2019).

Data privacy is another major ethical issue, particularly with the increasing use of personal data in AI applications. Ensuring that data is collected and used responsibly, in compliance with regulations such as General Data Protection Regulation (GDPR), is essential for maintaining public trust (Tene and Polonetsky, 2012). Articles will explore best practices for data anonymization, consent management, and secure data storage and sharing.

7. Conclusion

By bridging the gap between traditional disciplines and cutting-edge data science, the IJDS aims to spearhead discussions, foster research collaborations, and disseminate knowledge that addresses both specialized and generalist interests. The diverse range of topics covered in this editorial—Agricultural Data Science, Health Sciences Data Science, Life Sciences Data Science, Forensic Sciences Data Science, and General Data Science—reflects the journal's commitment to exploring the multifaceted applications of data science and its transformative potential across various fields.

Each section highlights how data science can provide innovative solutions to complex challenges, from enhancing crop yields and improving healthcare delivery to advancing forensic investigations and understanding biological systems. By leveraging data analytics, ML, and AI, researchers can uncover new insights and drive progress in their respective fields. Furthermore, the emphasis on ethical considerations and data privacy ensures that these advancements are achieved responsibly and with respect for individual rights and societal values.

The integration of data science into these diverse domains underscores its versatility and impact, making it an essential tool for modern scientific inquiry. As the field continues to evolve, the IJDS will remain at the forefront, publishing cutting-edge research that pushes the boundaries of what is possible. By providing a platform for interdisciplinary collaboration and knowledge sharing, the journal aims to foster a global community of data scientists dedicated to advancing science and improving society.

We invite researchers, practitioners, and educators to contribute to this interdisciplinary endeavor, ensuring that the power of data science is harnessed ethically and effectively across all spheres of scientific inquiry. Whether you are developing new algorithms, applying data science techniques to solve real-world problems, or exploring the ethical implications of AI, your work has the potential to make a significant impact.

As we look to the future, the IJDS is committed to supporting the growth and development of the data science community. We encourage submissions that showcase novel research, innovative methodologies, and critical analyses that contribute to the ongoing discourse in the field. Together, we can drive innovation, promote ethical practices, and harness the power of data science to address the complex challenges of our time.

In conclusion, the IJDS is more than just a publication; it is a catalyst for change, a forum for innovation, and a beacon for ethical and responsible data science. We look forward to your contributions and to the exciting discoveries and advancements that will undoubtedly emerge from this collaborative effort. Let us continue to push the boundaries of knowledge, challenge the status quo, and make meaningful strides towards a better, data-informed world.

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Call for Papers

We are currently seeking submissions for the journal. We encourage contributions that not only showcase novel research and methodologies but also reflect on the challenges and opportunities that arise at the intersection of data science and diverse scientific, academic, and industrial domains. Submissions should be rigorous, innovative, and contribute significantly to advancing the field. For guidelines and submission details, please visit our 'Author Guidelines'.

The integration of data science into various scientific fields highlights its versatility and transformative potential. Each domain presents unique challenges and opportunities, underscoring the importance of tailored approaches to data analysis and application. Through interdisciplinary research and collaboration, IJDS seeks to harness the power of data science to drive innovation and address some of the most pressing issues of our time.

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References

Abrahart RJ and L See (2000) Neural network vs. ARMA modelling: constructing benchmark case studies of river flow prediction. Hydrological Processes 14 (11-12): 2107-2124.

Aebersold R and M Mann (2016) Mass-spectrometric exploration of proteome structure and function. Nature 537 (7620): 347-355.

Angles R and C Gutierrez (2008). Survey of graph database models. ACM Computing Surveys (CSUR) 40 (1): 1-39.

Barocas S, M Hardt, and A Narayanan (2019) Fairness and machine learning. Accessed June 20, 2024 at https://www.fairmlbook.org.

Baumer B (2015) A data science course for undergraduates: Thinking with data. The American Statistician 69 (4): 334-342.

Beebe NL (2009) Digital Forensic Research: The Good, the Bad and the Unaddressed. In: Peterson, G., Shenoi, S. (eds) Advances in Digital Forensics V. Digital Forensics 2009. IFIP Advances in Information and Communication Technology, vol 306. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-04155-6_2.

Bickmore TW, LM Pfeifer, and MK Paasche-Orlow (2018) Using computer agents to explain medical documents to patients with low health literacy. Patient Education and Counseling, 101 (8): 1420-1427.

Casey E (2011) Digital Evidence and Computer Crime: Forensic Science, Computers, and the Internet. ISBN 978-0-12-374268-1. Academic Press & Elsevier.

Chandola V, A Banerjee, and V Kumar (2009) Anomaly detection: A survey. ACM Computing Surveys (CSUR) 41 (3): 1-58.

Clark JS, SR Carpenter, M Barber, S Collins, A Dobson, JA Foley, DM Lodge, M Pascual, R Pielke, W Pizer, C Pringle, WV Reid, KA Rose, O Sala, WH Schlesinger, DH Wall, and D Wear (2001) Ecological forecasts: an emerging imperative. Science 293 (5530): 657-660. https://doi.org/10.1126/science.293.5530.657.

Collins FS and H Varmus (2015) A new initiative on precision medicine. New England Journal of Medicine 372 (9): 793-795.

Deisboeck TS, and L Zhang (2011) Multiscale modeling of cancer: computational approaches from the nanoscale to the whole organism. Wiley Interdisciplinary Reviews: Systems Biology and Medicine 3 (4): 323-336.

Doshi-Velez F, and B Kim (2017) Towards a rigorous science of interpretable machine learning. arXiv preprint arXiv:1702.08608. https://doi.org/10.48550/arXiv.1702.08608.

Esteva A, B Kuprel, RA Novoa, J Ko, SM Swetter, HM Blau, and S Thrun (2017) Dermatologist-level classification of skin cancer with deep neural networks. Nature 542 (7639): 115-118. https://doi.org/10.1038/nature21056.

FAO (2017) The future of food and agriculture: Trends and challenges. Food and Agriculture Organization of the United Nations.

Foley JA, N Ramankutty, KA Brauman, ES Cassidy, JS Gerber, M Johnston, ND Mueller, C O'Connell, DK Ray, PC West, C Balzer, EM Bennett, SR Carpenter, J Hill, C Monfreda, S Polasky, J Rockström, J Sheehan, S Siebert, D Tilman, and DPM Zaks (2011) Solutions for a cultivated planet. Nature 478 (7369): 337-342. https://doi.org/10.1038/nature10452.

Froehle CM and JA White (2014) Interruption and Forgetting in Knowledge-Intensive Service Environments. POMS. https://doi.org/10.1111/poms.12089.

Galante N, R Cotroneo, D Furci, R Cotroneo, D Furci, G Lodetti, and MB Casali (2023) Applications of artificial intelligence in forensic sciences: Current potential benefits, limitations and perspectives. Int J Legal Med 137: 445–458. https://doi.org/10.1007/s00414-022-02928-5.

Geradts Z (2018) Digital, big data and computational forensics. Forensic Sciences Research 3 (3): 179-182. https://doi.org/10.1080/20961790.2018.1500078.

Goodfellow IJ, J Pouget-Abadie†, M Mirza, B Xu, D Warde-Farley, S Ozair, A Courville, and Y Bengio (2014) Generative Adversarial Nets. In Advances in Neural Information Processing Systems (pp. 2672-2680).

Hardin J, R Hoerl, NJ Horton, D Nolan, B Baumer, O Hall-Holt, and MD Ward (2015) Data science in statistics curricula: Preparing students to "think with data". The American Statistician, 69(4), 343-353.

Hermes S, T Riasanow, EK Clemons, M Böhm, and H Krcmar (2020) The digital transformation of the healthcare industry: exploring the rise of emerging platform ecosystems and their influence on the role of patients. Business Research 13: 1033–1069. https://doi.org/10.1007/s40685-020-00125-x.

Hood L and M Flores (2012) A personal view on systems medicine and the emergence of proactive P4 medicine: predictive, preventive, personalized and participatory. New Biotechnology 29 (6): 613-624.

Huang J, C Pray, and S Rozelle (2002) Enhancing the crops to feed the poor. Nature 418: 678–684. https://doi.org/10.1038/nature01015.

Jain AK and J Feng (2011) Latent fingerprint matching. IEEE Transactions on Pattern Analysis and Machine Intelligence 33 (1): 88-100.

Kamilaris A, A Kartakoullis, and FX Prenafeta-Boldú (2018) A review on the practice of big data analysis in agriculture. Computers and Electronics in Agriculture 143: 23-37.

Karr JR, JC Sanghvi, DN Macklin, MV Gutschow, JM Jacobs, B Bolival, N Assad-Garcia, JI Glass, and Covert, M. W. (2012). A whole-cell computational model predicts phenotype from genotype. Cell 150 (2): 389-401.

Keesara S, A Jonas, and K Schulman (2020) Covid-19 and health care's digital revolution. New England Journal of Medicine 382 (23), e82. https://doi.org/10.1056/NEJMp20058.

Kitano H (2002) Computational systems biology. Nature 420: 206–210. https://doi.org/10.1038/nature01254.

Kumar R, M Luthra, and RK Kesharwani (2018) Blockchain criminology: An analysis of blockchain technology in the domain of criminal investigation. In Advances in Smart Grid and Renewable Energy (pp. 317-324). Springer.

LeCun Y, Y Bengio, and G Hinton (2015) Deep learning. Nature 521 (7553): 436-444. https://doi.org/10.1038/nature14539.

Litjens G, T Kooi, BE Bejnordi, AA Setio, F Ciompi, M Ghafoorian, JAWM van der Laak, B van Ginneken, and CI Sánchez (2017) A survey on deep learning in medical image analysis. Medical Image Analysis 42: 60-88. https://doi.org/10.1016/j.media.2017.07.005.

Lobell DB, W Schlenker, and J Costa-Roberts (2011) Climate trends and global crop production since 1980. Science 333 (6042): 616-620. https://doi.org/10.1126/science.1204531.

Marx V (2013) Biology: The big challenges of big data. Nature 498 (7453): 255-260. https://doi.org/10.1038/498255a.

Montanaro A (2016) Quantum algorithms: An overview. npj Quantum Inf 2, 15023. https://doi.org/10.1038/npjqi.2015.23.

Mulla DJ (2013) Twenty-five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. Biosystems Engineering 114 (4): 358-371. https://doi.org/10.1016/j.biosystemseng.2012.08.009.

Obermeyer Z and EJ Emanuel (2016) Predicting the future—big data, machine learning, and clinical medicine. New England Journal of Medicine 375 (13): 1216-1219.

Obermeyer Z, B Powers, C Vogeli, and S Mullainathan (2019) Dissecting racial bias in an algorithm used to manage the health of populations. Science 366 (6464): 447-453.

Pan SJ and Q Yang (2010) A survey on transfer learning. IEEE Transactions on Knowledge and Data Engineering 22 (10): 1345-1359.

Pettorelli N, WF Laurance, TG O'Brien, M Wegmann, H Nagendra, and W Turner (2014) Satellite remote sensing for applied ecologists: opportunities and challenges. Journal of Applied Ecology 51 (4): 839-848.

Raza A, A Razzaq, SS Mehmood, X Zou, X Zhang, Y Lv, and J Xu (2019) Impact of Climate Change on Crops Adaptation and Strategies to Tackle Its Outcome: A Review. Plants 2019, 8, 34; https://doi.org/10.3390/plants8020034.

Richmond KM (2021) AI, Machine Learning, and International Criminal Investigations: The Lessons From Forensic Science. iCourts Working Paper Series, No. 222, Available at SSRN: https://ssrn.com/abstract=3727899 Or http://dx.doi.org/10.2139/ssrn.3727899.

Roden DM, HL McLeod, MV Relling, MS Williams, GA Mensah, JF Peterson, and SL Van Driest (2011) Pharmacogenomics. The Lancet 380 (9852): 507-520.

Safran C, M Bloomrosen, WE Hammond, S Labkoff, S Markel-Fox, PC Tang, and DE Detmer (2007) Toward a national framework for the secondary use of health data: an American Medical Informatics Association white paper. Journal of the American Medical Informatics Association 14 (1): 1-9.

Schlenker W and MJ Roberts (2009) Nonlinear temperature effects indicate severe damages to US crop yields under climate change. PNAS 106 (37): 15594-15598.

Shilo S, H Rossman, and E Segal (2020) Axes of a revolution: challenges and promises of big data in healthcare. Nature Medicine 26 (1): 29-38.

Stolfo SJ, W Fan, W Lee, A Prodromidis, and PK Chan (2000) Cost-based modeling for fraud and intrusion detection: Results from the JAM project. DARPA Information Survivability Conference and Exposition 2: 130-144.

Sutton RS and AG Barto (2018) Reinforcement Learning: An Introduction. MIT press.

Tai LH, U Kruger, and EJ Jacobs (2014) Comparison of gunshot residue distribution patterns on hands and associated clothing of suicides and homicides. Forensic Science International 239: 7-14.

Tene O and J Polonetsky (2012) Privacy in the age of big data: A time for big decisions. Stanford Law Review Online, 64, 63.

Topol EJ (2019) High-performance medicine: the convergence of human and artificial intelligence. Nature Medicine 25 (1): 44-56.

Turner W, S Spector, N Gardiner, M Fladeland, E Sterling, and M Steininger (2015) Remote sensing for biodiversity science and conservation. Trends in Ecology & Evolution 28 (5): 334-343.

Visscher PM, NR Wray, Q Zhang, P Sklar, MI McCarthy, MA Brown, and J Yang, (2017) 10 years of GWAS discovery: biology, function, and translation. American Journal of Human Genetics 101 (1): 5-22.

Wang L, N Pedroni, and E Zio (2018) Integrating health data into predictive maintenance of industrial systems: from failure-time distribution estimation to degradation analysis. IEEE Transactions on Reliability 67 (1): 283-294.

Webber H, T Gaiser, and F Ewert (2014) What role can crop models play in supporting climate change adaptation decisions to enhance food security in Sub-Saharan Africa? Agricultural Systems 127: 161-177. https://doi.org/10.1016/j.agsy.2013.12.006.

Westbrook JK, JD Lopez, SJ Fleischer, PD Lingren, and RL Meagher (2016) Modeling seasonal migration of fall armyworm moths. Int J of Biometeorology 60 (2): 255-267.

Wilhelm M, J Schlegl, H Hahne, A Moghaddas Gholami, M Lieberenz, MM Savitski, E Ziegler, L Butzmann, S Gessulat, H Marx, T Mathieson, S Lemeer, K Schnatbaum, U Reimer, H Wenschuh, M Mollenhauer, J Slotta-Huspenina, JH Boese, M Bantscheff, A Gerstmair, F Faerber, and B Kuster (2014) Mass-spectrometry-based draft of the human proteome. Nature 509 (7502): 582-587. https://doi.org/10.1038/nature13319.

Yang Z and B Rannala (2012) Molecular phylogenetics: principles and practice. Nature Reviews Genetics 13 (5): 303-314.

Zhang C, D Walters, and JM Kovacs (2019) Applications of low altitude remote sensing in agriculture upon vertical take-off and landing (VTOL) systems: A review. Remote Sensing 11 (3): 320.