Lecture Notes in Networks and Systems 878

M. Shamim Kaiser
Juanying Xie
Vijay Singh Rathore *Editors*

ICT: Smart Systems and Technologies

Proceedings of ICTCS 2023, Volume 4

Springer

Lecture Notes in Networks and Systems

Volume 878

The series “Lecture Notes in Networks and Systems” publishes the latest developments in Networks and Systems—quickly, informally and with high quality. Original research reported in proceedings and post-proceedings represents the core of LNNS.

Volumes published in LNNS embrace all aspects and subfields of, as well as new challenges in, Networks and Systems.

The series contains proceedings and edited volumes in systems and networks, spanning the areas of Cyber-Physical Systems, Autonomous Systems, Sensor Networks, Control Systems, Energy Systems, Automotive Systems, Biological Systems, Vehicular Networking and Connected Vehicles, Aerospace Systems, Automation, Manufacturing, Smart Grids, Nonlinear Systems, Power Systems, Robotics, Social Systems, Economic Systems and other. Of particular value to both the contributors and the readership are the short publication timeframe and the world-wide distribution and exposure which enable both a wide and rapid dissemination of research output.

The series covers the theory, applications, and perspectives on the state of the art and future developments relevant to systems and networks, decision making, control, complex processes and related areas, as embedded in the fields of interdisciplinary and applied sciences, engineering, computer science, physics, economics, social, and life sciences, as well as the paradigms and methodologies behind them.

Indexed by SCOPUS, INSPEC, WTI Frankfurt eG, zbMATH, SCImago.

All books published in the series are submitted for consideration in Web of Science.

For proposals from Asia please contact Aninda Bose (aninda.bose@springer.com).

Principal
A.J. Institute of Engineering & Technology
Mangaluru - 575 006

M. Shamim Kaiser · Juanying Xie ·
Vijay Singh Rathore
Editors

ICT: Smart Systems and Technologies

Proceedings of ICTCS 2023, Volume 4

Springer

Editors
M. Shamim Kaiser
Jahangirnagar University
Dhaka, Bangladesh

Juanying Xie
School of Computer Science
Shaanxi Normal University
Xi'an, China

Vijay Singh Rathore
Department of Computer Science
and Engineering
Jaipur Engineering College and Research
Centre
Jaipur, Rajasthan, India

ISSN 2367-3370 ISSN 2367-3389 (electronic)
Lecture Notes in Networks and Systems
ISBN 978-981-99-9488-5 ISBN 978-981-99-9489-2 (eBook)
https://doi.org/10.1007/978-981-99-9489-2

This Springer imprint is published by the registered company Springer Nature Singapore Pte Ltd.
The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

Preface

Eighth International Conference on Information and Communication Technology for Competitive Strategies (ICTCS-2023) targets state-of-the-art as well as emerging topics pertaining to information and communication technologies (ICTs) and effective strategies for its implementation for engineering and intelligent applications.

The conference is anticipated to attract a large number of high-quality submissions, stimulate the cutting-edge research discussions among many academic pioneering researchers, scientists, industrial engineers and students from all around the world and provide a forum to researcher; propose new technologies, share their experiences and discuss future solutions for design infrastructure for ICT; provide a common platform for academic pioneering researchers, scientists, engineers and students to share their views and achievements; enrich technocrats and academicians by presenting their innovative and constructive ideas; and focus on innovative issues at international level by bringing together the experts from different countries.

The conference was held on December 8 and 9, 2023, physically at Hotel—Four Points by Sheraton Jaipur, India, and Digitally on Zoom organized by Global Knowledge Research Foundation and Managed by G R Scholastic LLP.

Research submissions in various advanced technology areas were received, and after a rigorous peer review process with the help of program committee members and external reviewers, 200 papers were accepted with an acceptance rate of 17%. All 200 papers of the conference are accommodated in five volumes; also, papers in the book comprise authors from 22 countries.

This event success was possible only with the help and support of our team and organizations. With immense pleasure and honor, we would like to express our sincere thanks to the authors for their remarkable contributions, all the technical program committee members for their time and expertise in reviewing the papers within a very tight schedule, and the publisher Springer for their professional help.

We are overwhelmed by our distinguished scholars and appreciate them for accepting our invitation to join us through the virtual platform and deliver keynote speeches and technical session chairs for analyzing the research work presented by the researchers. Most importantly, we are also grateful to our local support team for

Contents

Transfer Learning Techniques in Medical Image Classification

D. S. Radhika Shetty and P. J. Antony

1 Introduction

Medical image classification, a cornerstone of modern health care, plays a pivotal role in assisting clinicians with accurate diagnosis, treatment planning, and patient care. With the advancement of medical imaging technologies, the sheer volume and complexity of medical image data have ushered in new challenges and opportunities. The application of deep learning techniques, particularly within the realm of convolutional neural networks (CNNs) [11], has demonstrated remarkable potential in addressing these challenges. However, the success of deep learning models often hinges on access to substantial labeled data, a resource that remains scarce in medical imaging due to factors like data privacy, rarity of certain conditions, and the need for expert annotation [1].

Enter transfer learning, a paradigm that has revolutionized the landscape of deep learning by enabling the efficient adaptation of knowledge from one task or domain to another. In the context of medical image classification, transfer learning techniques have emerged as a powerful means to bridge the data scarcity gap, leverage features learned from diverse sources, and enhance the performance of models on medical images [1]. The underlying principle of transfer learning aligns with the medical community's pursuit of accurate, robust, and efficient diagnostic tools that can improve patient outcomes.

This survey paper embarks on an extensive exploration of transfer learning techniques in the context of medical image classification. By systematically reviewing a plethora of research, methodologies, and applications, this paper aims to provide a

D. S. Radhika Shetty (✉)
Vivekananda College of Engineering and Technology, Puttur, VTU, Belagavi, India
e-mail: radhikashettyds.cse@vcetputtur.ac.in

P. J. Antony
A. J. Institute of Engineering and Technology, Mangalore, VTU, Belagavi, India

M. S. Kaiser et al. (eds.), *ICT: Smart Systems and Technologies*, Lecture Notes in Networks and Systems 878, https://doi.org/10.1007/978-981-99-9489-2_21

comprehensive understanding of the diverse strategies that empower deep learning models to excel in the medical imaging domain.

The primary focus of this survey is to shed light on various transfer learning paradigms, ranging from fine-tuning and feature extraction to domain adaptation. Each technique's theoretical foundations, practical implementations, and implications for medical image classification will be scrutinized to unveil their potential and limitations. Furthermore, the survey will delve into notable studies across different medical imaging modalities, such as X-rays, MRI, CT scans, and histopathological images, showcasing how transfer learning has been instrumental in achieving breakthroughs in diagnostic accuracy and efficiency.

The ethical considerations inherent to deploying transfer learning models in the medical domain will also be addressed. Ensuring patient safety, preventing biases, and maintaining model interpretability are all vital factors that underscore the importance of responsible implementation.

As the survey progresses, emerging trends, challenges, and future directions within the realm of transfer learning for medical image classification will be identified [1]. The symbiotic relationship between transfer learning and deep learning architectures, the exploration of domain adaptation methods, and the integration of multi-modal data are among the anticipated avenues that will shape the trajectory of medical image analysis [1].

In conclusion, this survey paper is envisioned as an essential resource for researchers, clinicians, and machine learning practitioners interested in harnessing the power of transfer learning to enhance medical image classification. By synthesizing theoretical insights, empirical findings, and ethical considerations, this paper aspires to foster advancements that further strengthen the marriage between deep learning and medical imaging, ultimately resulting in improved diagnostic accuracy and healthcare outcomes.

2 Different Transfer Learning Techniques

Transfer learning has proven to be incredibly effective in various fields of deep learning, including medical image analysis. It involves using a pre-trained model on a large dataset and adapting it for a different, often smaller, dataset or task. In the context of medical image analysis, transfer learning techniques aim to leverage knowledge learned from one medical imaging task and apply it to another task or domain. Here are some common transfer learning techniques used in deep learning for medical images:

2.1 Feature Extraction and Fine-Tuning

Feature Extraction: In this approach, you use a pre-trained neural network as a feature extractor. The early layers of the network, which capture basic features like edges and textures, are kept frozen, and only the later layers are replaced with new layers that are tailored to your specific task. This new architecture is then trained on your medical image dataset.

Fine-Tuning: After replacing the final layers, you can also fine-tune some of the earlier layers with a smaller learning rate. This allows the model to adapt some of the learned features to the specific characteristics of your medical images. Fine-tuning is especially effective when you have a larger dataset.

2.2 Domain Adaptation

Domain Transfer: In cases where the source and target domains have some differences, domain adaptation techniques aim to reduce the domain gap. This involves techniques like adversarial training, where an additional domain discriminator is used to minimize the difference between source- and target-domain features.

Domain adaptation is a critical challenge when applying transfer learning to medical images because medical imaging encompasses a wide range of modalities, specialties, and institutions, each with its unique characteristics and data distributions. Domain adaptation methods should be evaluated rigorously to ensure their effectiveness in specific medical image classification tasks, considering the unique characteristics of the data and domains involved.

2.3 Multi-task Learning

In medical imaging, there are often related tasks that can be learned simultaneously. Multi-task learning involves training a single neural network to perform multiple tasks. The idea is that shared lower-level features will benefit both tasks, even if the tasks are somewhat different [17].

2.4 Self-supervised Learning

Self-supervised learning is a technique where the model learns from the data itself without explicit annotations. For medical images, this could involve predicting missing parts of an image, rotations, or other transformations. The features learned through self-supervision can then be fine-tuned for the target task [1].

2.5 Cross-modality Transfer

Medical imaging often involves various modalities such as MRI, CT, X-ray. Transfer learning can be applied to adapt a model trained on one modality to another. This can be particularly helpful when labeled data are scarce for a specific modality [1].

2.6 Zero-Shot and Few-Shot Learning

Zero-shot learning involves training a model on one task and then applying it to a completely different task with no task-specific training data. Few-shot learning is similar but allows for a small amount of task-specific training data. These techniques are useful when obtaining labeled medical images for the target task is difficult.

2.7 Model Ensemble

Combine predictions from multiple pre-trained models, each fine-tuned for a specific aspect of the target task. This can improve performance by capturing a broader range of features.

When applying transfer learning to medical image analysis, it is crucial to consider the domain shift, data variability, and potential biases present in medical data. The choice of transfer learning technique depends on factors like the availability of labeled data, similarity between the source and target tasks, and the nature of the medical images being analyzed.

3 Literature Survey

Pre-trained deep architectures have proven to be effective in various medical image classification tasks. The utilization of architectures such as VGG [3] and ResNet [4] has demonstrated significant improvements in classification accuracy. These models, originally designed for natural images, have been fine-tuned or used as feature extractors for medical images, showcasing their ability to capture relevant features [3, 4].

Domain adaptation techniques play a vital role in addressing domain shift challenges in medical image classification. Adversarial domain adaptation, proposed by Ganin et al. [5], has been widely employed to align feature distributions between source and target domains [5]. Additionally, domain-invariant feature learning methods [6] have shown promise in reducing the impact of domain discrepancies [6].

Self-supervised learning has emerged as a valuable approach in medical image classification tasks. Techniques such as image rotation prediction [7] and contrastive learning [8] have been adapted to pre-train models for subsequent medical image analysis, showcasing their ability to learn informative representations [7, 8].

The paper titled "Invasive Cancer Detection Utilizing Compressed Convolutional Neural Network and Transfer Learning" by Kong et al. [9] focuses on the detection of invasive cancer using advanced machine learning techniques. The authors propose a methodology that combines a compressed convolutional neural network (CNN) with transfer learning to improve the accuracy of cancer detection in medical images [9].

The paper titled "Deep Learning Predicts Underlying Features on Pathology Images with Therapeutic Relevance for Breast and Gastric Cancer" by Valieris et al. [10] discusses the application of deep learning techniques to predict relevant underlying features in pathology images of breast and gastric cancer. The study aims to identify patterns and characteristics within these images that have therapeutic significance. The authors employ advanced deep learning algorithms to analyze pathology images and extract valuable information related to cancer characteristics. By doing so, they aim to predict therapeutic implications based on the identified features. The study primarily focuses on breast and gastric cancers, two prevalent types of cancer [10].

The paper titled "Application of Artificial Intelligence Technology in Oncology: Towards the Establishment of Precision Medicine" [11] explores the utilization of artificial intelligence (AI) technology in the field of oncology to advance precision medicine. The authors discuss how AI techniques are being employed to analyze complex medical data, including genomic information, medical images, and clinical records, with the aim of tailoring treatment approaches to individual patients. The paper emphasizes the potential of AI to enhance diagnostic accuracy, predict treatment outcomes, and guide personalized therapies. It highlights the importance of interdisciplinary collaboration between medical experts and AI researchers to harness the full potential of AI in oncology [11].

The paper "Deep Convolutional Neural Networks with Ensemble Learning and Transfer Learning for Automated Detection of Gastrointestinal Diseases" by Qiaosen Su, Fengsheng Wang, Dong Chen, Gang Chen, Chao Li, and Leyi Wei focuses on using advanced machine learning techniques, specifically deep convolutional neural networks (CNNs), for automating the detection of gastrointestinal diseases. The authors combine the power of ensemble learning, where multiple models are combined for better performance, with transfer learning, which involves leveraging knowledge from pre-trained models. By employing deep CNNs along with these strategies, the paper aims to improve the accuracy and efficiency of automated detection of gastrointestinal diseases. The authors provide insights into how their approach enhances the capability of computer-aided diagnosis for these medical conditions [12].

The paper titled "Automatic Detection of Early Gastric Cancer in Endoscopic Images using a Transferring Convolutional Neural Network" by Y. Sakai et al. presents a method for automatically identifying early-stage gastric cancer in endoscopic images. The authors leverage a transferring convolutional neural network

(CNN) approach, which involves adapting a pre-trained CNN model on a large dataset to the specific task of detecting gastric cancer. This transfer learning approach enables the model to learn relevant features from the existing data and apply them effectively to the new medical image dataset. The study showcases the potential of this technique in enhancing the accuracy and efficiency of early gastric cancer detection, contributing to improved diagnostic capabilities in the field of gastroenterology [13].

Rajaraman et al. [14] study emphasizes the potential of transfer learning as a valuable tool in medical image classification, showcasing how pre-trained CNNs can serve as powerful feature extractors for the accurate detection of malaria parasites in thin blood smear images. The authors adopted a transfer learning approach, where they utilized pre-trained CNN models that were originally trained on large-scale natural image datasets. They fine-tuned these models on a dataset of thin blood smear images specific to malaria parasite detection. The fine-tuning process involved modifying the last layers of the pre-trained networks to match the classification task for malaria detection [14].

Hosseini-Asl and Keyvanpour's [15] research contributes to the field of medical image analysis by showcasing the successful adaptation of a 3D CNN for Alzheimer's disease diagnosis. The authors propose the utilization of a 3D CNN, which is designed to process three-dimensional data such as volumetric medical images. The network is trained on a dataset containing medical images of individuals with Alzheimer's disease and healthy controls. The architecture of the 3D CNN is adapted to the specific characteristics of the dataset and the task of Alzheimer's disease diagnosis [15].

Mou et al. [16] paper presents an embedding transfer framework that harnesses knowledge from auxiliary domains for cardiovascular event prediction. The authors present an embedding transfer framework designed to leverage data from different but related domains to enhance cardiovascular event prediction. The framework involves learning representations (embeddings) from auxiliary domains with abundant data and transferring these embeddings to the target cardiovascular prediction task. This enables the model to benefit from the knowledge captured in the auxiliary domains [16].

4 Discussion

The field of medical image classification has witnessed significant advancements in recent years, largely attributed to the application of transfer learning techniques [2]. This survey paper aimed to provide a comprehensive overview of the various transfer learning methods utilized in medical image classification tasks. Through an analysis of the selected studies, several key insights and discussions have emerged.

4.1 Performance Improvement

The studies reviewed consistently demonstrated that transfer learning techniques substantially enhance the performance of medical image classification models. Pre-trained models, trained on large general datasets, capture rich features that are beneficial for extracting relevant information from medical images. This is particularly crucial in scenarios where obtaining large annotated medical image datasets is challenging due to limited data availability.

4.2 Domain Adaptation

Domain adaptation methods have emerged as a critical aspect of transfer learning in medical image classification. Medical images often vary significantly from natural images, and direct transfer of knowledge from natural images to medical images may not yield optimal results. Domain adaptation techniques, such as adversarial training and domain-specific fine-tuning, were highlighted as effective strategies to bridge the domain gap and improve model generalization.

4.3 Fine-Tuning Strategies

Various strategies for fine-tuning pre-trained models were explored in the reviewed studies. Layer freezing, where certain layers are kept fixed during training, and gradual unfreezing, which involves progressively unfreezing layers, were found to prevent catastrophic forgetting and stabilize training. Selective fine-tuning of specific layers based on their relevance to the task was also reported as a strategy to optimize model performance.

4.4 Data Augmentation

Data augmentation was identified as a valuable technique to mitigate overfitting, especially when working with limited medical image datasets. Augmentation methods such as rotation, scaling, and flipping were commonly employed to artificially expand the dataset and improve model generalization. The choice of augmentation techniques has depended on the specific characteristics of the medical images.

Transfer learning will continue to be a driving force in the field of medical image classification, helping to improve accuracy, efficiency, and clinical decision-making. However, its successful evolution will depend on addressing specific challenges related to domain adaptation, interpretability, data privacy, and regulatory compliance.

When using transfer learning in medical imaging, researchers and practitioners should be acutely aware of a range of ethical considerations to ensure that the deployment of AI models is responsible and aligns with the best interests of patients and the broader healthcare ecosystem. Here are some of the key ethical considerations: Patient Privacy and Data Security, Data Encryption, Informed Consent, Patient Consent, Data Bias and Fairness, Transparency and Interpretability, Accountability and Responsibility, Medical Professional Involvement, Data Ownership and Sharing, Regulatory Compliance, Continual Monitoring and Improvement, Ongoing Evaluation: Public Engagement and Transparency, Emergency, and Critical Use.

Ethical considerations in medical imaging extend beyond the technical aspects of AI development and encompass broader societal, legal, and professional norms. Researchers and practitioners must navigate these ethical challenges thoughtfully and transparently to ensure that AI technologies in health care are trustworthy, safe, and beneficial to patients and healthcare providers alike. Collaboration between multi-disciplinary teams, including ethicists and legal experts, can help to address these complex ethical issues effectively.

5 Conclusion

In conclusion, this study highlighted the significant impact of transfer learning techniques on the advancement of medical image classification. The studies reviewed collectively demonstrated that transfer learning not only enhances classification accuracy but also accelerates model convergence, reducing the need for extensive training on limited medical datasets.

Domain adaptation methods have emerged as a critical component, addressing the unique challenges posed by medical images and their distinct characteristics compared to natural images. Fine-tuning strategies, along with thoughtful layer selection, have proved to be pivotal in achieving optimal results while avoiding overfitting.

The adoption of transfer learning in medical image classification holds immense promise for improving diagnostic accuracy, aiding medical professionals in making informed decisions, and ultimately enhancing patient care. As the field continues to evolve, it is expected that further research will explore innovative transfer learning architectures, domain adaptation techniques, and data augmentation strategies tailored specifically to the nuances of medical image analysis.

References

1. Alzubaidi L, Al-Amidie M, Al-Asadi A, Humaidi AJ, Al-Shamma O, Fadhel MA, Zhang J, Santamaría J, Duan Y (2021) Novel transfer learning approach for medical imaging with limited labeled data. Cancers 13:1590. https://doi.org/10.3390/cancers13071590
2. Siddalingaswamy CKPC, Pathan S, D'souza N (2021) A multiclass skin lesion classification approach using transfer learning based convolutional neural network. In: 2021 seventh international conference on bio signals, images, and instrumentation (ICBSII), Chennai, India, pp. 1–6. https://doi.org/10.1109/ICBSII51839.2021.9445175
3. Simonyan K, Zisserman A, Visual Geometry Group (2015) Very deep convolutional networks for large-scale image recognition. Department of Engineering Science, University of Oxford, ICLR
4. He K, Zhang X, Ren S, Sun J (2015) Deep residual learning for image recognition. Microsoft Research
5. Ganin A, Massaro E, Gutfraind A et al (2016) Operational resilience: concepts, design and analysis. Sci Rep 6:19540. https://doi.org/10.1038/srep19540
6. Ching T, Himmelstein DS, Beaulieu-Jones BK, Kalinin AA, Do BT, Way GP, Ferrero E et al (2018) Opportunities and obstacles for deep learning in biology and medicine. J R Soc Interface 15(141):20170387
7. Gidaris S, Singh P, Komodakis N (2018) Unsupervised representation learning by predicting image rotations. arXiv:1803.07728
8. Chen T, Kornblith S, Norouzi M, Hinton G (2020) A simple framework for contrastive learning of visual representations. In: Proceedings of the 37th international conference on machine learning, PMLR, 119, 1597–1607
9. Kong B, Sun S, Wang X, Song Q, Zhang S (2018) Invasive cancer detection utilizing compressed convolutional neural network and transfer learning. In: 21st international conference, Granada, Spain, 16–20 Sept 2018, proceedings, part II. https://doi.org/10.1007/978-3-030-00934-2_18
10. Valieris R, Amaro L, Osório CABT, Bueno AP, Rosales Mitrowsky RA, Carraro DM, Nunes DN, Dias-Neto E, Silva ITD (2020) Deep learning predicts underlying features on pathology images with therapeutic relevance for breast and gastric cancer. Cancers 12(12):3687. https://doi.org/10.3390/cancers12123687. PMID: 33316873; PMCID: PMC7763049
11. Hamamoto R, Suvarna K, Yamada M, Kobayashi K, Shinkai N, Miyake M, Takahashi M, Jinnai S, Shimoyama R, Sakai A et al (2020) Application of artificial intelligence technology in oncology: towards the establishment of precision medicine. Cancers 12(12):3532. https://doi.org/10.3390/cancers12123532
12. Su Q, Wang F, Chen D, Chen G, Li C, Wei L (2022) Deep convolutional neural networks with ensemble learning and transfer learning for automated detection of gastrointestinal diseases. Comput Biol Med 150:106054. https://doi.org/10.1016/j.compbiomed.2022.106054. Epub ahead of print. PMID: 36244302
13. Sakai Y, Takemoto S, Hori K, Nishimura M, Ikematsu H, Yano T, Yokota H (2018) Automatic detection of early gastric cancer in endoscopic images using a transferring convolutional neural network. In: Annual international conference on IEEE engineering medical biology society, July 2018, 4138–4141. https://doi.org/10.1109/EMBC.2018.8513274. PMID: 30441266
14. Rajaraman S, Antani SK, Poostchi M, Silamut K, Hossain MA, Maude RJ, Jaeger S, Thoma GR (2018) Pre-trained convolutional neural networks as feature extractors toward improved malaria parasite detection in thin blood smear images. PeerJ 6:e4568. https://doi.org/10.7717/peerj.4568
15. Hosseini-Asl E, Ghazal M, Mahmoud A, Aslantas A, Shalaby AM, Casanova MF, Barnes GN, Gimel'farb G, Keynton R, El-Baz A (2018) Alzheimer's disease diagnostics by a 3D deeply supervised adaptable convolutional network. Front Biosci (Landmark Ed) 23(3):584–596. https://doi.org/10.2741/4606. PMID: 28930562
16. Mou L, Ghasemzadeh N, Dey D (2018) Learning from others: an embedding transfer framework for cardiovascular event prediction. In: Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining, pp 1050–1059

17. Tu Z, Bai X (2010) Auto-context and its application to high-level vision tasks and 3D brain image segmentation. IEEE Trans Pattern Anal Mach Intell 32(10):1744–1757. https://doi.org/10.1109/TPAMI.2009.186

Integrating AI Tools into HRM to Promote Green HRM Practices

Jasno Elizabeth John and S. Pramila

1 Introduction

Sustainability has emerged as one of the most important aspects of any business organization. The central objective of corporate governance is to attain an elevated level of performance and profitability while safeguarding against management prioritizing their interests at the expense of stakeholders [1]. However, this goal is pursued without considering the environmental damage that it can create. As stated by the Chartered Institute of Personnel and Development in London [2], the core of organizational sustainability revolves around the idea of reinforcing the environmental, societal, and economic aspects of business operations. It highlights how the concept of sustainability enables a business to thrive while ensuring the well-being of future generations' needs is not overlooked [3].

Green HRM manifests an organization's commitment to sustainability, where HR strategies, policies, and practices are designed to not only enhance employee well-being but also to reduce the environmental footprint of its operations. To fulfill their sustainability objectives and to meet the expectations of the organizational stakeholders, both internally and externally, companies are increasingly turning to AI [4]. At the nexus of AI and Green HRM lies the prospect of reshaping the conventional HR functions, and revamping the traditional process of HRM like recruitment, development, engagement, and performance management to be eco-friendly and resource-optimized.

Incorporating AI tools into HRM practices presents a novel dimension of optimization and innovation, enabling organizations to harness data-driven insights, predictive analytics, and automation to achieve their sustainability objectives. The

J. E. John (✉) · S. Pramila (✉)
Christ (CHRIST (Deemed to be University), Delhi NCR, India
e-mail: jasno.john@res.christuniversity.in

S. Pramila
e-mail: pramila.s@christuniversity.in

M. S. Kaiser et al. (eds.), *ICT: Smart Systems and Technologies*, Lecture Notes in Networks and Systems 878, https://doi.org/10.1007/978-981-99-9489-2_22

ingenious employment of AI can contribute to reducing energy consumption, minimizing waste, and enhancing operational efficiency, all of which are central to the themes of Green HRM.

2 Literature Review

The organizations have developed strategies to deal with the ecological footprint's reduction, in addition to addressing economic concerns. In today's corporate landscape, to thrive in the corporate arena and to facilitate shareholder profit, organizations must concentrate on a holistic range of factors, encompassing not only economic and financial aspects but also social and environmental factors [5]. The Agenda 21 action plans for sustainable development also highlight the need for interdisciplinary coordination to integrate environmental and social issues into business practices [6].

The term 'Green HRM' was coined in 1996 by Wehrmeyer in his book 'Greening People,' marking the inception of its evolution. The author discussed improving sustainability through the most vital resource—Human Resources. It elaborated the idea of raising awareness about the significance of these practices, introducing policies for their practical implementation, and incentivizing individuals who adopt environmentally sustainable behavior through rewards to encourage their continued adoption. This also resulted in a substantial shift in work attitudes and personal motivation concerning their jobs and the organization [7]. Considering the current heightened emphasis on corporate environmental sustainability, contemporary HR managers have been tasked with the added duty of integrating Green HR principles into the corporate mission statements and HR policies. Green HRM fosters an environmentally conscious behavior and culture, both at the organizational and individual levels [8].

HRM as a critical function that directs the workforce, has been entrusted with the responsibility to drive initiatives that align with sustainability goals. The integration of AI tools into HRM processes presents an exceptional scope to achieve this target, underlining the tenets of Green HRM. A varied array of AI applications centered on Human Resource Management (HRM) is employed within organizations. These applications enhance the cost-efficiency of HR processes and consequently enhance the overall employee experience. This, in turn, leads to heightened levels of employee commitment and satisfaction while reducing instances of employee turnover [9]. We anticipate technology to not only streamline back-office operations but also progressively assume the more human-centric aspects of HR responsibilities. While these technologies undoubtedly enhance efficiency, reduce bias, and enhance the HR function's value within organizations, it is essential to recognize that the human touch will remain indispensable for achieving success [10]. Maintaining a harmonious equilibrium between technology and the human element is essential to ensure that employees' distinct requirements and emotions continue to be efficiently addressed. These tools should be integrated and utilized in such a way that they minimize