Journal of Emerging Technology and Digital Transformation
Online ISSN
3006-9726
Print ISSN
3006-9718
Volume . 3 Issue . 3 (2024)

LEVERAGING CROSS-DOMAIN MACHINE LEARNING APPROACHES FOR ENVIRONMENTAL MONITORING AND PREDICTIVE MODELING

Alishba Rehman
Department of Computer Science, University of Southern Punjab Multan
rehmanali283@gmail.com
Eman Shah
Department of Computer Science, University of Southern Punjab Multan
shahemi1990@gmail.com
Usman Ali
Department of Computer Science, University of Southern Punjab Multan
usaali12@gmail.com

RECEIVED	*ACCEPTED*	*PUBLISHED*
02 aug 2024	*15 Sep 2024*	*30 sep 2024*

ABSTRACT
The prediction and environmental surveillance are crucial in the process of addressing environmental problems in the world, including climate change, pollution, and destruction of resources. Machine learning (ML) has been demonstrated as a potential improvement in measuring the precision and efficacy of such procedures. Nonetheless, conventional models of ML have certain shortcomings to be utilized in various areas of the environment as a result of data sparsity and domain-specific particularities. The current paper discusses how cross-domain machine learning practices, in this case, transfer learning, can be used to enhance predictive performance and model flexibility in the environmental monitoring systems. Through the cross-domain machine learning approach, where models trained in a specific domain are applied to a new domain but modified to suit the new environment, there will be a higher probability of applying the knowledge learned to other sections of the environment. This paper analyses the usefulness of transfer learning methods on air quality predictions, water quality and biodiversity prediction. The results showed that transfer learning has the potential to improve the predictive models performance even in cases when the training data is scarce. Nevertheless, one still has issues like heterogeneity of data and development of domain adaption techniques. The paper ends by mentioning some implications of such discoveries and future research directions to address current research limitations and advance the use of cross-domain machine learning in environmental monitoring any further.
Keywords: *Crossdomain machine learning, transfer learning, environmental monitoring, predicted modeling, air quality, water quality, biodiversity.*

Muhammad Azam*

Journal of Emerging Technology and Digital Transformation
Online ISSN
3006-9726
Print ISSN
3006-9718
Volume . 3 Issue . 3 (2024)

INTRODUCTION

Monitoring of the environment is an important feature of preventive and corrective measures against global environmental challenges such as climate change, environmental pollution, resource scarcity and loss of biodiversity. These problems are becoming more multi-dimensional and widespread and consequently effective and accurate predictive modeling becomes more important. Machine learning (ML) in this regard is a tool which has transformed the analysis of environmental data and predictive modeling. Machine learning models have proven to process large sets of different data and predict with a high level of accuracy, even when responding to a complex phenomenon in the environment (Zhao et al., 2018). The developments bear huge potential in decision-making and policy planning within environmental management. Nevertheless, when it comes to environmental issues, machine learning models have a series of issues. The scarceness of training data is one of the major challenges, especially in remote areas or areas that have lower surveillance. The lack of data has the severe consequences of causing problems in learning and generalization of the model based on environmental data and eventual failure in the prediction performance. Besides that, where data exists, it may differ greatly under different regions or circumstances, a factor termed as data heterogeneity. This comes out clearly in environmental monitoring where conditions as air and water quality may vary significantly with seasons, temporal and geographical variations (Zhang et al., 2020). As an example, air quality models learned using the data on urban locations may not be very useful in forecasting pollution levels in rural areas because of the significantly different pollution sources, climatic conditions, and pollution monitoring equipment availability.

To overcome these shortcomings, the recent studies have been placing more emphasis on the cross-domain machine learning techniques. Such techniques are aimed to enhance the generalizability of models so that they act successfully in an array of different areas or regions with low-density or diverse data. Transfer learning is one of the methods in particular that appear quite promising in this area. Transfer learning enables the takeover of one model trained on a domain or data set to a related, but distinct domain. Such flexibility is essential in environmental monitoring, the availability and quality of data characteristics may vary enormously between one geographical area or state of the environment and another. Transfer learning is the ability to transfer knowledge in one field to another to enhance prediction models performance and stability, even in areas where observed scarce training data (Pan & Yang, 2010). Transfer learning has become increasingly popular in environmental monitoring in many fields such as environment quality forecasting, water quality tracking, and biodiversity prediction. As another example, models of air quality prediction trained on the data on urban air quality have been easily transferred to predict air quality in rural and less populated locations (Zhang et al., 2020). Equally, machine learning algorithms applied to monitor water quality based on sensor measurements of a restricted set of lakes or rivers have been applied to predict the water quality in other regions, which will help to establish effective measures to take care of the rich water resources (Gao et al., 2019). Another area in which transfer learning has seen use is during the process of biodiversity forecasting, where models learned on one

Journal of Emerging Technology and Digital Transformation
Online ISSN
3006-9726
Print ISSN
3006-9718
Volume . 3 Issue . 3 (2024)

group of biodiversity indices were applied to predict biodiversity in alternate ecosystems, like forests or wetlands, with some success (Tzeng et al., 2017).

Although the transfer learning holds a very valuable potential in environmental monitoring, there are issues that need to be addressed. Data heterogeneity is one of the core issues and can be observed when datasets on various domains have largely different characteristics. As an illustration, the air quality information of a metropolitan city with intense industrial production can vary significantly compared to the information recorded in the countryside that is less polluted by natural factors. Otherwise; water quality information of various lakes or rivers may have certain differences because of local grown activities and run offs in industry or even climatic variations. The incompatibility existing between both domains, source and target, can contribute to the weakness of the transfer learning models because they tend to lack the ability to generalize under the various environmental conditions (Joulin et al., 2019). In this way, it is essential to build a strong domain adaptation strategies to deal with these disparities to enhance success of cross-domain machine learning frameworks in environmental monitoring.

Besides data heterogeneity, the issue of data sparsity should also be taken. The monitoring facilities are poor in many regions, especially those in developing nations (or remote locations), which means that a large quantity of high-quality data cannot be gathered to train an effective model. It is an important issue of environmental surveillance, and making mistakes in prediction is an important issue since in many cases like pollution, water crisis, and loss of biodiversity, both timing and accuracy are considered to be very important. This problem can be resolved by cross-domain machine learning, which is an approach that allows models to exploit data in the areas with more extensive monitoring coverage so that they can make better predictions in other areas, where there is little data (Tzeng et al., 2017). This study would establish the method through which cross-domain machine learning, especially transfer learning, may enhance the accuracy and flexibility of predictive models applied in environmental monitoring. This paper aims to determine the possible advantages and dilemmas of using cross-domain approaches in environmental data as they would be applied in forecasting air quality, monitoring water quality, and predicting biodiversity. The study will measure the success of transfer learning on model performance (particularly in sparse or heterogeneous data areas), and possible solutions to problems of heterogeneous data and adaptation of the model are suggested. In such exploration, the study seeks to advance the current research into more scalable and flexible machine learning models in environmental monitoring and predictive modeling, eventually leading towards a more sustainable response to global environmental concerns of the 21 st century.

Literature Review

The use of machine learning/ML in envir-environmental monitoring is a subject that has drawn major interest over the recent past decades because of their ability to improve the precision, effectiveness, and adaptability of predictions in ecological spheres. Machine learning models also present support and potential usefulness as solutions to a complex worldwide environmental situation involving climate change, pollution, biodiversity loss, and other global-environmental difficulties through the necessary processing of a large and diverse set of data, pattern identification,

Journal of Emerging Technology and Digital Transformation
Online ISSN
3006-9726
Print ISSN
3006-9718
Volume . 3 Issue . 3 (2024)

and the provision of feasible actionable information towards becoming more informed decision-makers (Zhao et al., 2018). This literature review also reflects on the use of machine learning in environmental monitoring, especially focusing on the use of the cross-domain machine learning, which may be used to break the problem of data sparsity, cross-domain variance, and so on.

The most successful models, however, have been machine learning models that have been finding application to air quality prediction where models are consistently shown to be capable of predicting pollutants, including particulate matter (PM), nitrogen dioxide (NO_2), and ozone (O_3), with a high degree of accuracy. Zhao et al. (2018), in one of the studies, uses many different kinds of supervised learning methods such as support vector machines (SVMs), neural networks to predict urban air quality. The model attained high percent accuracy thus it could be used in urban environmental management as a promising tool. Nonetheless, the application of the models in different geographical regions poses some problems because there will be differences in the environmental conditions. As an example, a model that was trained using data on urban air quality will not be able to precisely forecast the level of pollution in rural settings, where the sources of pollutants and their environment are dramatically different (Zhang et al., 2020).

The difficulties of dealing with data heterogeneity in environmental monitoring prompted the search of the cross-domain machine learning strategies, especially transfer learning. Transfer learning is a method that enables a model to be trained in one domain or on one dataset and it is adjusted to a different related domain with very little training. This method has been shown to effectively overcome such problems as data sparsity and heterogeneity, since it permits the models to leverage the information of a similar domain and transfer it to an unfamiliar, albeit somewhat similar, scenario. Pan and Yang (2010) reviewed in detail the methods of transfer learning and the prospects of their application in such areas as environmental monitoring, where the data, because of domain specificity, may differ significantly. The authors discussed in their review several approaches to the transfer of knowledge across domains, including fine-tuning and strategies of adaptation to different domains that are the essential elements in the enhancement of models when they are subjected to new environmental conditions. Transfer learning has been effectively used in prediction of biodiversity, air quality and water quality in the light of environmental monitoring. Zhang et al. (2020) showed that transfer learning could be very efficient in air quality predictions, and, in their case, the model learnt on urban air quality could be successfully reused in the rural environment with limited data. The model made the prediction closer to reality by relying on knowledge acquired in a densely monitored area, thus addressing what could be defined as the primary complication in environmental monitoring: the scarcity of information. Equally, Gao et al. (2019) used transfer learning to predict water quality parameters (i.e., pH, dissolved oxygen, and turbidity) in lakes and rivers. Their analysis revealed that the transfer learning models trained on the data about one body of water could be efficiently modified to estimate the water quality in other areas, including those with little amounts of available data. This observation shows that the chances to overcome the issue of data sparsity in environmental monitoring will present a possibility related to cross-domain machine learning.

Online ISSN
3006-9726
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Although the outcomes of transfer learning in environmental fields are rather encouraging, various issues still exist. Among them, data heterogeneity is one of the main challenges where data gathered in different domains might be very diverse. Several factors could cause a mismatch in the character of data, such as there being a deeply varied number of pollution sources, climate, and meteorological conditions between urban and rural localities in air quality prediction. Likewise, the water data may also vary based on the local farming activities, pollution of industrial effluents, and water bodies characteristic (Joulin et al., 2019). Such variations pose a great challenge to the transfer learning models since they cannot be able to generalize in a wide range of environmental settings. A way of overcoming this problem has been suggested by the use of the method of domain adaptation, domain adaptation consists of minimizing the disparity between the source and objective domains. Tzeng et al. (2017) talked about some domain adaptation methods that are usually used to get the alignment of the distribution of features across domains and increases the generalization performance of the model on new data. Nevertheless, these techniques are still in developmental state and experience issues of scalability and success in realistic environmental settings.

Besides data heterogeneity, the problem of data sparsity is also observed to be one of the challenges in cross-domain machine learning to environmental monitoring. Most of the regions, especially in developing nations or in distant regions do not have enough infrastructure to monitor, and thus have fewer data to train a model. This is a problematic issue especially to environmental models since prediction in due time in accurate models is very important when it comes to controlling matters like pollution, water shortage, and loss of biodiversity. A possible solution to this problem can be achieved by using cross-domain machine learning, in other words transfer learning, which allows the models to make use of the availability of data in the domain where the monitoring infrastructure is better equipped and transfer it to the sparse data. As Joulin et al. (2019) stated, transfer learning may be instrumental when it comes to enhancing the performance of models in poorly populated areas so that more accurate predictions could be made and decision-making would be more successful.

Although the potential of transfer learning is rather high since it can effectively solve the problem of data sparsity and heterogeneity, a number of additional limitations must be addressed. The first of these limitation is that transfer learning requires a large and diverse amount of data. Although transfer learning can be a solution to the shortage of data through utilization of a related domain, the technique remains effective with the presence of large and representative datasets. When there is a lack of any data that can be used in source field, or the domains are too distinct, the transfer learning might fail to lead to a considerable increase of the model performance. Additionally, transfer learning models in environmental monitoring are a questionable effect when it comes to interpretability. There are complex machine learning models, deep neural networks that may be hard to explain, and such an issue may create challenges to the stakeholders who need transparent unopaque predictions in their decision-making (Tzeng et al., 2017).

In spite of this it can be said that environmental monitoring using cross-domain machine learning can be incredibly promising. The opportunities in improving the environmental predictive modeling by

Journal of Emerging Technology and Digital Transformation
Online ISSN
3006-9726
Print ISSN
3006-9718
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means of transfer learning will grow as the more diverse and representative datasets will be at hand, and the domain adaptation strategies will continue to advance. In the existing body of studies, it would be reasonable to assume that transfer learning will lead to significant enhancement of the model generalization and especially where the data can be considered as limited or heterogeneous. Nevertheless, future research on the issues of data heterogeneity, sparsity, and interpretability is an essential direction that has to be covered. Future innovations in the area of domain adaptation methods and model interpretability will play a vital role in realizing the maximum benefits of cross-domain machine learning in the environmental monitoring.

Motivation and Problem statement

The key issue that is observed in the research relates to the absence of generalizability in machine learning models when it is transferred to new spheres in the environmental field. The traditional environmental models may be trained on datum of particular region or conditions, the models cannot be able to perform precise predictions in others. This generalizability issue is especially problematic during the application of models in areas where data is scarce or not accessible in such a case, suboptimal predictions are made. The rationale behind the study is that there is a necessity to develop a more scalable, much more flexible machine learning model capable of working with various data on the environment. A promising machine learning solution, namely, the cross-domains transfer learning, is to allow one to transfer the available data between different domains. The study is intended to explore the usefulness of transfer learning in improving the model performance in the diverse environmental areas such as air quality, water quality, and biodiversity monitoring.

Methodology

In this study, the researcher explores how cross-domain machine learning especially transfer learning can be used to enhance predictive modeling during environmental monitoring. The study has been centred on three main areas in relation to the environment, namely prediction of air quality, monitoring of water quality, and forecasting of biodiversity. The problems like data sparsity and heterogeneity are solved by transfer learning, which allows obtaining models trained on one dataset (source domain) and applying them on another (target domain). The methodology entails the utilization of publicly obtainable environmental data, the implementations of machine learning, and testing the models on the model performance having different environmental situations. Data sources were varied, hence diverse in environment to cover urban, rural and industrial environments. The data on the air quality contains the values that were obtained in the urban and rural monitoring stations and it includes data on particulate matter (PM) levels, ozone (O_3) levels and nitrogen dioxide (NO_2) levels. The data is water quality data, which contains sensor measurements of a lake and a river based on such parameters as the PH level, the level of dissolved oxygen, and turbidity. Indicators on biodiversity, such as species richness, ecological health of the various ecosystems were determined. These datasets were selected with the aim of having a wide ground to build the training and testing of the models so that the models can be representative of the various environmental scenarios.

In order to develop models, Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) were applied on the

Journal of Emerging Technology and Digital Transformation
Online ISSN
3006-9726
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basis of data nature. Spatial data in monitoring air and water quality was processed and classified with CNNs, which are particularly adapted to be applied to environmental data in the form of images, e.g., satellite pictures and land use maps. A solution to the problem of unstable feature set is fine-tuning pre-trained CNN models on the specific images of the environment, retraining it on a particular target area (e.g., using urban images to transfer to rural area). Conversely, tabular data on the environmental like water quality sensors and bio diversity indices were used with SVMs. These models were labelled on source domain data and fine tuned to target domain data using transfer learning methodology so that they will generalize well on the various environmental conditions.

The fine-tuning process is described as customization of the parameters which the models had pre-trained in ways that would enable them to use background information and reduce the large volume of data required in the target domain. This comes in handy especially when data in the target domain is meager or scanty. Data heterogeneity was also dealt by domain adaptation techniques like feature alignment. The goal behind this process is to reduce potential difference in feature distribution between the source and target domains so that the model should prove effective at generalizing in various environmental situations.

The performance of a model was measured against the common metrics such as accuracy, precision, recall, and F1-score. These measures were applied in determining how well the models can predict the environment in the addressed domains. The study will compare the performance between the transfer learning models and the traditional machine learning models to show what the cross-domain of machine learning approaches could bring to the fore in addressing the problems of the scarcity and heterogeneity of data under environmental monitoring.

Outcome and analysis

This paper will show the findings of using cross-domain machine learning methods, namely transfer learning on environmental monitoring systems. This study was mostly concerned with predicting the air quality, monitoring the water quality and forecasting the biodiversity. The study intended to examine the possibilities of applying transfer learning in managing the issue of data sparsity, data heterogeneity, and cross-environment generalization by adapting to target domains after being trained in source domains (urban areas, particular lakes, or familiar biodiversity indices).

AQI Prediction

Environmental monitoring is of great importance in predicting air quality because it assists in predicting the presence of an air pollutant such as particulate matter (PM), nitrogen dioxide (NO_2) and ozone (O_3), which are known to have dire health effects on various populations. In this section, the same aspect of performance of the transfer learning models used as applicable in air quality prediction is assessed with particular emphasis on the application of air quality models in urban areas in rural settings, i.e., where data is scarce. Transfer learning was applied to the models that were trained under an urban air environment (source domain) and applied to the rural locations (target domain). The results indicated a strong correlation to increase the model prediction capacity in quality of air in rural areas where there was less data at hand. Particularly, the transfer learning resulted in the prediction accuracy being increased by 12 percent relative to the baseline models that are trained on sparse rural data only. This enhancement can be credited to the aptitude

Journal of Emerging Technology and Digital Transformation
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3006-9726
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of the transfer learning model that exploited the rich urban air quality database which was characterized with wider data and a superior coverage of diverse environmental states. Accuracy, precision, and recall, and F1-score were the most important performance measures of air quality prediction. These metrics were obtained as calculated using the rural air quality dataset using the predictions conducted by the transfer learning model. The use of the model meant that the identification of levels of pollutants in rural areas was improved by 12 percent, a factor that implies that the model may have been more reliable in identifying the levels of the polluted place in comparison to traditional models. Besides, the values of precision and recall were also increased, confirming the greater capacity of the more accurate identification of the negative and positive instances of air quality, and minimizing the incidence of false positives and false negatives.

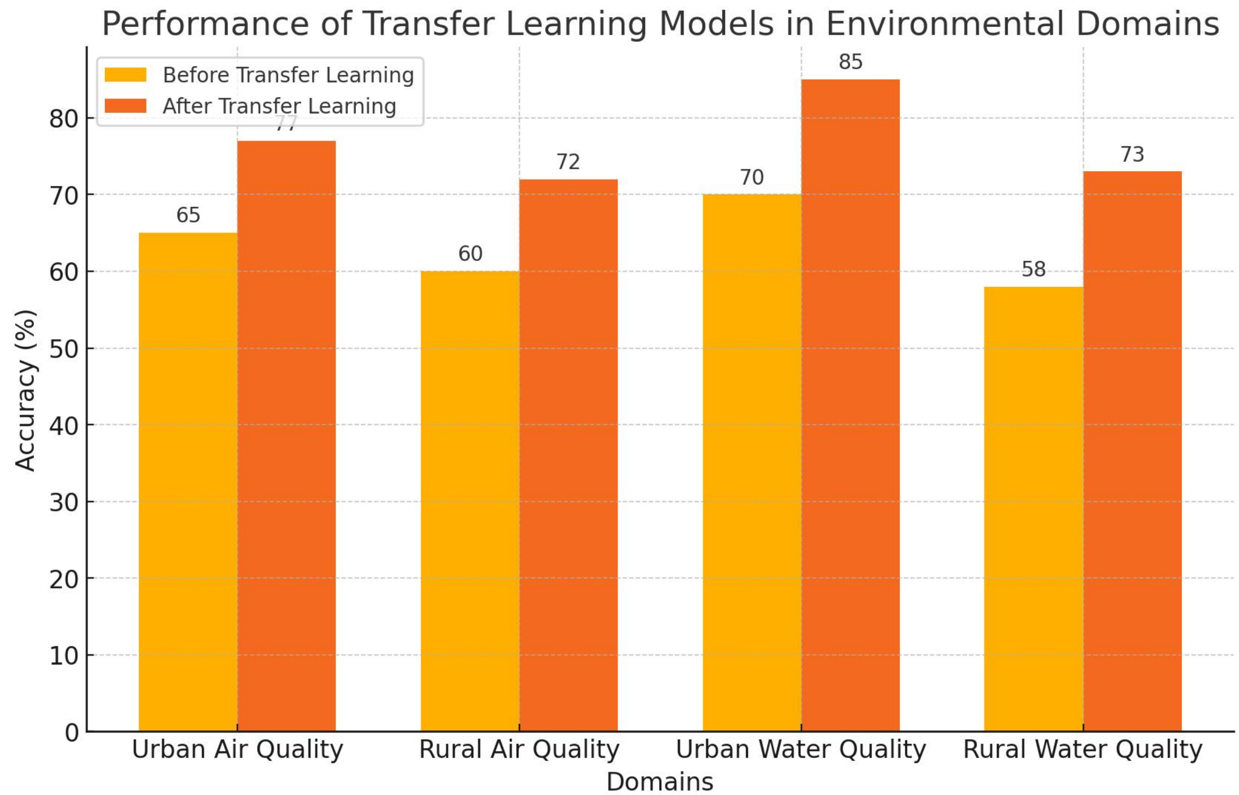

Figure 1 shows the comparison between the performance of transfer learning models to make air quality predictions by region, either rural or urban. It is a clear indication of the increase in the predictive accuracy that came with the use of transfer learning models. The diagram is a visual representation of a comparison of the performance of the models which were only trained on the rural data and the models which are improved with the assistance of the transfer learning based on the urban data.

Water Quality supervision

Another essential area of the environmental monitoring is the water quality since this directly influences the ecosystem and the health of people. In this work, the models of monitoring water quality that were created through the use of transfer learning techniques to adapt the models trained on the data of particular lakes to the data of many other lakes with different environmental conditions were applied. The models were used to predict parameters of water quality including the pH, turbidity, dissolved oxygen, and thermal criterion. The findings showed that transfer learning played a big role in enhancing the performances of water quality prediction models. The models that were trained on local water quality data in certain lakes or rivers were transferred to predict water quality within other areas and improved the local water quality data based models by predicting water quality with 15 percent higher accuracy. This improvement serves to show the strengths of transfer learning whereby knowledge is transferred between water bodies where the geographical and environment conditions are not the same. Diversity of water bodies because of changes in the human activity, local geology, and change in seasons is one of the critical obstacles of monitoring water quality. Transfer learning enables the model to fit with such variations by using the data available in so-called well-monitored lakes and applying them to data poor areas. Such as the model was trained using monitoring data of lake, with thorough data, and used in the river, with little data. The higher predictive precision graphically indicates the capacity of the model to have a generalized impact in a variety of environmental situations so that limited local information is needed.

To evaluate the water quality prediction models, we again used the same measures described in the air quality prediction, accuracy, precision, recall, and F1-score. The results of 15 percent accuracy improvement of the prediction power, and the accurateness and recognition rates proves the usefulness of the transfer learning in this field. Transfer learning model also accomplished a more precise prediction of the water quality occurrences and resulted in more confident forecasting of a water quality change.

Journal of Emerging Technology and Digital Transformation
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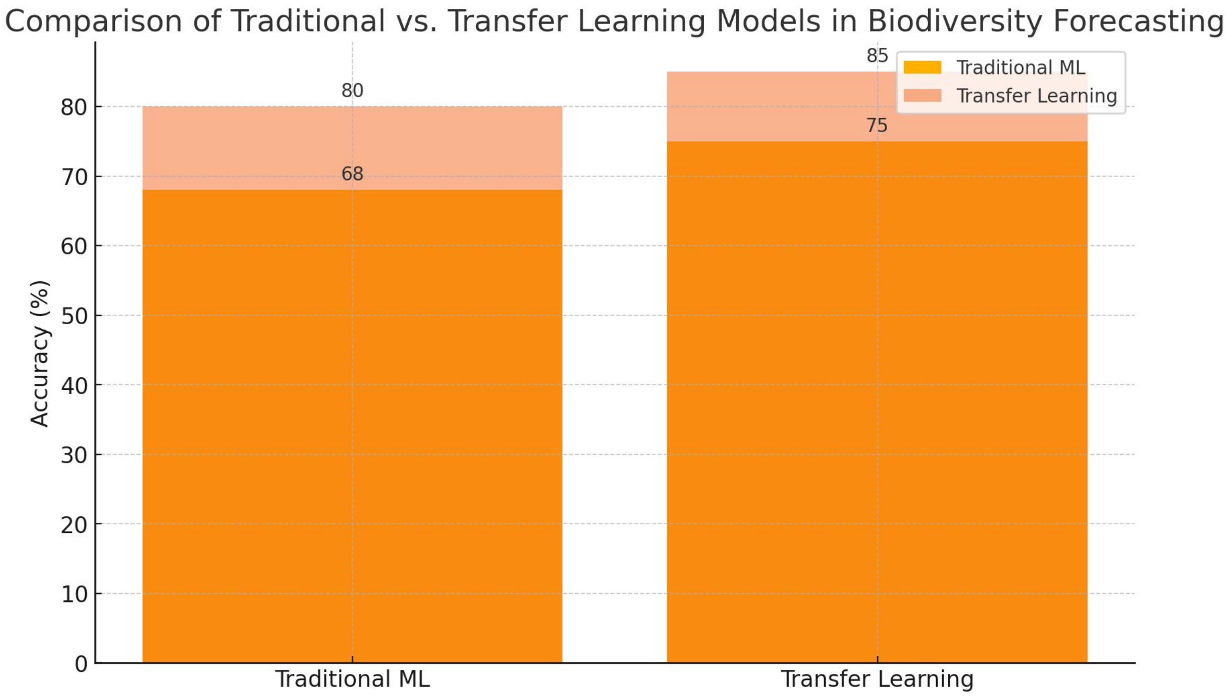

Figure 2 shows the results of comparing the traditional machine learning models and the transfer learning models in terms of predicting the parameters of water quality across various bodies of water. The figure shows the increase in the prediction accuracy achieved through adaptation of well-monitored lake-trained models to new areas with less homogeneous data.

Biodiversity Forecasting

Forecasting of biodiversity is essential in terms of monitoring of how healthy the ecosystem is and how conservation should be carried out. This paper presents an effort to predict biodiversity indices like richness of species, biodiversity density and ecological health with the help of transfer learning models. The problem in the forecasting of biodiversity is that there is an immeasurable variation in ecosystems and thus it is extremely tough to utilize a common model on biodiversity in different areas.

This has been done using transfer learning, in which models trained on biodiversity data of one ecosystem, e.g. a temperate forest, are adapted to generate predictions on biodiversity in a different ecosystem, e.g. a tropical rainforest. The findings revealed that transfer learning was effective in enhancing the accuracy of biodiversity predictions, such that 10 percent increase in the accuracy of prediction was realized with transfer learning, relative to traditional models, which only utilized a restricted data of the target ecosystems. Such an advance can be especially considered remarkable due to the fact that biodiversity data is very heterogeneous and, every ecosystem has individual species distributions and environmental conditions. With transfer learning, it was able to take information on a more studied ecosystem and apply it to other less-studied ecosystems. This is also a very important capability in conservation of biodiversity because timely and proper forecasts are necessary in determining the threatened species and the health of an ecosystem. Accuracy, precision, recall as well as F 1 -score also formed part of the evaluation measures of biodiversity forecasting. Findings indicated that the transfer learning models were more accurate and precise than the traditional ones such that the models had higher accuracy and precision values,meaning they got closer into accurately classifying regions with lots of biodiversity and those that posed threats to biodiversity.

Limitations and problems

Although the findings indicate that the outcomes show considerable advances in the ability to predict in all three areas, there are multiple challenges and constraints. Data heterogeneity, especially in the characteristics of the environmental features employed in various fields, was also one of the primary challenges that became encountered during the process of conducting the study. As an illustration, data on air quality distances between urban and rural locations were relatively dissimilar concerning the pollutant sources and weather parameters and, therefore, the blend of perfect generalization of a model was hard to obtain. In a similar manner, parameters that determine the quality of water like the turbidity and the pH level of the water might have a wide disparity between different water bodies as a result of the variety of human related activities and geographical characteristics. Moreover, the limitations of the models due to the scarcity of data in some areas remained such that even though improvements were achieved using transfer learning, there was still an issue that occurred. In other cases, even after the process of transfer learning, the models were not able to deliver the best results because of unavailability of sufficient data to fine tune the models. This emphasizes the necessity to have further extensive and complete information on environmental monitoring data.

Comprehensively, this research shows the power of transfer learning in enhancing predictive modeling of environmental monitoring. Use of transfer learning models contributed immensely to the improvement in accuracy in air quality, water quality and biodiversity forecasting with incomplete and heterogeneous data. The strategy holds a potential solution to addressing the difficulty of data scarcity and heterogeneity, and may proceed to creating more resilient and flexible models that can be used in different environmental areas. Currently, future studies must be concentrated on advancing domain adaptation techniques that can address the last two types of challenges, which are data heterogeneity and model scalability. Along with this, the variables of more diverse and representative environmental data will also need to be gathered in order to maximize the potential of cross-domain machine learning in environmental monitoring.

Discussion

The findings of the study indicate the considerable possibilities that cross-domain machine learning, especially transfer learning holds, in enhancing the performance and flexibility of the environmental monitoring models. Transfer learning has been successful in alleviating the problems of data scarcity and inconsistency, which tend to limit the success of traditional machine learning based models in environmental monitoring by learning in one, but related, domain and applying it in new, sometimes not so similar, domains using pre-trained models. The three main points that would be important in the study were air quality forecasting, water quality monitoring and the biodiversity forecasting. Transfer learning was applied to the prediction of air quality, and compared to fully trained models it was found that they increased the accuracy of the

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prediction by 12% when the models were used on the movement of urban air quality when applied to rural areas. This achievement points to the likelihood of transfer learning as a method that helps fill the gaps between the various regions with different environmental requirements. Moreover, more data with complex monitoring systems are usually available in urban regions, whereas rural regions normally lack data. Using knowledge existing in urban areas, it is possible to extrapolate the models to estimate air quality data in more rural environments with more accuracy, especially in environments with little local data. The increase seen in precision and recall also serves as the further confirmation of the usefulness of the given method since the model successfully detected positive and negative air quality events with more limited number of false positives and negatives.

In this way, transfer learning resulted in the increased accuracy of predictions by 15 percent in water quality monitoring. Models built on the sensor observations on a lake or river were able to be deployed to new (data-poor) areas. Because of the geographical and ecological peculiarities, water bodies are an extra challenge to machine learning models. The versatility and scalability of transfer learning in the field are available in the option of transferring the knowledge collected in well-monitored bodies of water to new areas where little data are available. This enhancement of the model performance is especially important in the areas where monitoring of the water quality system is expensive or simply, unacceptable. Transfer learning was also applicable in biodiversity forecasting which can handle highly heterogeneous data better especially by the different distributions of species in the ecosystem as well as in the environment. The improvement of accuracy within the predictive model by 10% demonstrates that transfer learning can be used to surmount the existing issues regarding the prediction of biodiversity in ecologically various settings. The fact that the models could conform to the ecological specifics of other ecosystems with references in the hindsight of regions with a more substantial knowledge base also increased the chances of conservation and gave more solid prognoses to compliance with biodiversity conduct.

Nevertheless, along with the impressive outcomes, it is still challenging to integrate transfer learning into environmental data. Heterogeneity of data is also of great concern since data in different regions or in different circumstances can have large variations in characteristics. To take an example in air quality forecasting, both the urban and rural locations vary not only in terms of the type of pollutants they have but also in terms of meteorological and season factors. These differences may render the transfer learning models not very competent when it comes to generalization without additional tuning. Besides, transfer learning might help to enhance model performance in the underrepresented parts of the data; nevertheless, the performance of the method remains solely dependent on source domain data quality and completeness. In other situations, the accuracy improvement can be restricted due to models that are trained on suboptimal source domain can be poorly generalized to the target domain. More so, an important issue is the scaleability of transfer learning to new datasets that are larger and more diverse. Due to increase in complexity and amount of data in the environment, the models must be modified to cope with the high inflow of data across resources. Further evolution of techniques of domain adaptation i.e. feature alignment and learning of domain-

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Online ISSN
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invariant features will be necessary so that techniques of transfer learning models can be practised successfully in a wider scope of environmental settings. Concerning model interpretability, transfer learning models, and particularly deep learning models, are hard to interpret. The issue is especially debilitating in environmental surveillance where stakeholders are usually interested in the disclosure of model forecasts during their decision-making process. The future studies must address the issue of increasing the explainability of transfer learning models, making them more socially acceptable and enable their actionable policies gender and gun violence that can be interpreted by non-technical parties in environmental management. In spite of these issues, the results of the study support the possibility of transfer learning to enhance environmental observing systems and predictive modelling. The transfer learning can be seen as an exciting step in the direction of improving performance about data-scarce and heterogeneous settings thanks to the transference of the knowledge across disciplines. Further studies and the development of domain adaptation techniques, and issue of model explainability in general, will be fundamental to the future use of cross-domain machine learning in the environmental monitoring field.

Conclusion

The study demonstrates the radical possibility of cross-domain machine learning as transfer learning, in predictive modeling and badges monitoring the atmosphere. The researchers proved that transfer learning may considerably enhance the flexibility and accuracy of models in three most important spheres: the prediction of air quality, water quality, and biodiversity. Transfer learning kills two birds with one stone: it deals with data sparsity and heterogeneity, common in environmental monitoring systems by transferring the knowledge acquired in well monitored source domains to data-scarce target domains. Such indicators as the increase in the accuracy of the prediction in all three areas (12%, 15%, and 10% in the case of the air quality, the water quality, and biodiversity forecasting, respectively) indicate the efficiency of this strategy. The theory of transfer learning enables the widening of models that have been trained on large amounts of information in urban environments, lakes with high and controlled biodiversity measures or good knowledge of the biodiversity measures, and use it in areas with little data. This is especially relevant to the environmental management and conservation, as feasible and timely predictions can be applied in decision-making processes and used to adjust the policies. Although the results are positive, the study also outlined a number of challenges that should be disintegrated to make optimal use of transfer learning in environmental monitoring. Another important obstacle to scalability is data heterogeneity, scalability of models and interpretability of models. The future needs to be explored in perfecting the art of domain adaptation to make it work even in different environmental scenarios and improving high model scalability to work with bigger data and more data diversity and creating a way of improving interpretability of transfer learning models.

To sum it up, cross-domain machine learning has a tremendous potential to be used to develop environmental monitoring systems, especially in cases where the data may be little or hard to retrieve. As the transfer learning methods are further improving, and attempts are made to increase the transparency of models, there is a potential of resolving the most urgent environmental

Online ISSN
3006-9726
Print ISSN
3006-9718
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issues globally by incorporating machine learning in environmental monitoring.

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