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Transfer Learning In Machine Learning: A Review Of Methods And Applications

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Abstract

Transfer learning has gained significant traction and popularity in the field of machine learning due to its wide range of potential applications. This review article offers a thorough examination of transfer learning techniques and their wide-ranging applications in several fields. This text provides a thorough evaluation of the literature, focusing on important research and the methodology used. Furthermore, a comparative table highlighting transfer learning research across several areas provides valuable insights into the wide range of applications. The inclusion criteria were centred on recent articles published within the past five years that comprehensively examined transfer learning methodologies, applications, frameworks, problems, and future directions. The review articles highlight the widespread use of transfer learning models, the effectiveness of data augmentation strategies, and the capability of transfer learning to tackle issues particular to different domains. Nevertheless, some constraints like as biases in the dataset, difficulties in interpreting the model, and problems with scalability have been recognised. These limitations provide opportunities for future research to focus on creating transfer learning algorithms that are more resilient and easier to read.

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A. Introduction

Transfer learning is a form of machine learning that utilizes pre-existing, transferable information from other similar jobs to facilitate the learning of a distinct activity with a limited amount of data [1]. Transfer learning is a crucial approach in machine learning that has transformed the discipline by allowing models to utilize information from one domain and apply it successfully to another [2] [3]. Machine learning methods often need a significant quantity of labelled data for training, rendering them less feasible in situations where data is scarce or costly to get [4] [5] . Transfer learning is a technique that enables models to apply information acquired from a domain with a large amount of data to a domain with a little amount of data. This improves the model's performance and ability to generalize [6]. Transfer learning is highly important in several fields such as healthcare, image recognition, natural language processing, and robotics [7]. Transfer learning has enabled significant advancements in illness detection and personalized medication within the healthcare field. It does this by transferring information from extensively researched datasets to fresh medical imaging or genetic datasets [8]. The present review aims to provide a detailed analysis of the various approaches and techniques used in transfer learning. This course will examine the fundamental concepts of transfer learning, which include domain adaptation, fine-tuning, and model distillation. Moreover, it will explore sophisticated transfer learning methods, including advanced learning, meta-learning, and multi-task learning, emphasizing their impact on improving model performance and resilience. The present review aims to offer useful insights and an improved comprehension of the transformative effects of transfer learning by synthesizing existing literature and providing a comprehensive overview of transfer learning methods and applications. It is intended for researchers, practitioners, and enthusiasts in the field of machine learning. The purpose of this study is to provide a comprehensive overview of the offered solutions, emphasizing their distinctive and notable features. The evaluated articles include detailed descriptions of experiments conducted for practical applications, including testing of alternative solutions, and present the overall comparative outcomes of these studies.

This study has been separated into many sections to offer an organized review of transfer learning. Section B will explore the intricacies of transfer learning, emphasizing its importance and consequences, and this section also is dedicated to exploring different techniques of transfer learning. Section C provides an extensive literature review that simply summarizes the main findings from previous studies. Section D explores the difficulty of transfer learning encountered by the authors of the examined research. Furthermore, and alos this section presents a comparative analysis in the structure of a comparison table, which gives valuable insights into noteworthy transfer learning research conducted in many fields. Section E is specifically allocated to engage in conversations and present the outcomes, respectively. Section F contains the Conclusion and direction for the future

B. Research Method

1. Transfer learning

Gransfer learning (TL) is a concept in machine learning that aims to enhance the capacity of models to generalize by using knowledge from related tasks or domains [9],[10]. Given that machine learning models often need substantial quantities of training data, transfer learning might enhance prediction outcomes by additionally harnessing relevant data. Collecting precise target data for building an individual model can be expensive in many scenarios, such as for a particular people, machine, environment setting, or period. However, more generic data is easily accessible. Although it is customary in machine learning for test data to be sampled from the same distribution as the training data [11], transfer learning (TL) allows for the transfer of information from one domain to another that is similar. In addition, TL may also denote the transfer of information between distinct prediction tasks[12]. It has a connection with multitask learning, but with the distinction that activities are not equally significant. Instead, learning is optimized for a particular objective [13],[14]. The notion of transfer learning may have originated from the field of educational psychology. Psychologist C.H. Judd's theory of generalization of transfer states that learning to transfer happens when experiences are generalized. By generalizing their experiences, individuals may transfer the knowledge gained from one scenario to another. According to this hypothesis, transfer can only occur if there is a connection between two learning processes. For example, an individual who has acquired proficiency in playing the violin may acquire proficiency in playing the piano at a faster rate compared to others, due to the shared knowledge and abilities across both instruments . Figure 1 presents graphic illustrations of transfer learning to enhance understanding.

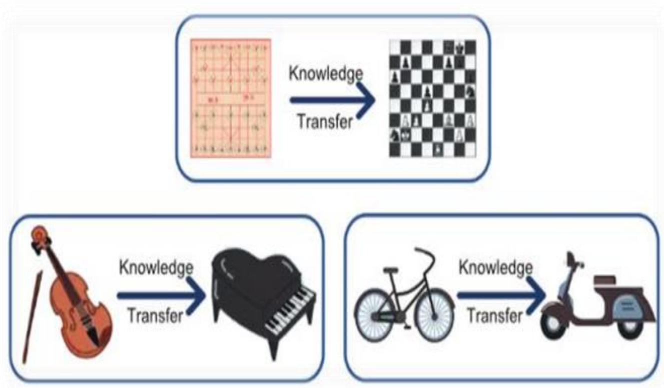

Figure 1. some examples of transfer learning [16].

Transfer learning is distinct from traditional methods of machine learning due to its emphasis on the exchange and transfer of information from a source model to a target model. As seen in Figure 2, traditional methods would deal with the source and target datasets as distinct entities and train an individual model for each dataset. On the other hand, a transfer learning strategy involves building a model using the source dataset and using that information to train a model for the target dataset [15].

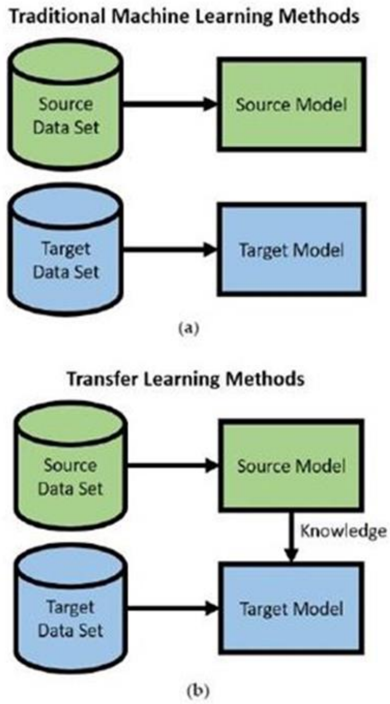

Figure 2. Illustration of the differentiation among traditional and transfer learning methods in the realm of machine learning. In the conventional approach (a), distinct models are trained for the source and target datasets without any kind of interaction

Utilizing transfer learning offers several advantages compared to traditional methods.

- By eliminating the necessity of training several machine learning models from the beginning for comparable tasks, one can save time and resources [16].
- The technology offers increased efficiency in resource-intensive tasks such as picture classification or natural language processing [17].
- To address the challenges arising from a scarcity of annotated training data, one might utilize pre-trained models [17].

2. TRANSFER LEARNING METHODS

Transfer learning involves addressing three main study inquiries on the timing, content, and methodology of knowledge transfer [18]. The "how to transfer" element may be classified into four primary categories of methods: instance-based, feature-based, model-based, and relation-based transfer learning [19].

2.1 Instance-Based Transfer Learning: refers to a method where a model is trained for the target domain by employing weighted combinations or resampled source domain data , [20] discusses TrAdaBoost and MultiSource-TrAdaBoost as examples of instance-based transfer learning algorithms. Wang et al., 2021 [21] introduced a transfer learning method based on instances to detect DDoS attacks. The suggested approach considers publicly available DDoS datasets as the primary source and chooses the most informative cases based on information gained for dimension reconstruction. The rebuilt features and target variables are combined as input for the TrAdaBoost algorithm using dimension reconstruction. It offers a very versatile DDoS detection technology that is effective in identifying previously unknown assault kinds.

2.2 Feature-Based Transfer Learning: This approach involves mapping data from both the source and destination domains into a shared feature space using specific feature representations. Deep transfer learning refers to a form of transfer learning that involves many strategies such as network-based, mapping-based, and adversarial-based deep transfer learning[22]. In their study, Mendigoria et al., 2021 [23], sought to categorize indigenous banana fruit by employing image-based deep transfer networks and conventional machine learning methods. The researchers obtained spectral, textural, and morphological characteristics and then reduced them to the two most important aspects using a hybrid method called NCA-PCA. The Classification Tree model achieved the highest accuracy of 91.28%, surpassing the accuracy of deep transfer networks. In general, the suggested machine learning method demonstrated potential for categorizing bananas after they had been harvested.

2.3 Model-Based Transfer Learning: This refers to the process of transferring models or model parameters across the source and target domains. Examples of model-based transfer learning include algorithms such as SAN (Selective Adversarial Network), PADA (Partial Adversarial Domain Adaptation), and UAN (Universal Adaptation Network) [24]. The approach suggested by Shan et al., 2021 [25] known as Model-Based Transfer Learning and Sparse Coding (MTLSC), is specifically developed for partial face recognition. The method utilizes mirrored pictures of the original probe samples to increase the sample size and use VGGNet, which has been pre-trained on the VGGFace dataset, to extract facial characteristics using model-based transfer learning. Subsequently, these characteristics are recreated by employing a sliding window technique to account for fluctuations in partial face dimensions. The method of sparse coding with rectification is utilized to compute the minimum scores for both probing and mirrored samples across all classes, resulting in an enhancement of the performance of partial face recognition. The efficacy of the MTLSC framework for partial face recognition is confirmed by experimental findings from several face and person re-identification databases.

2.4 Relation-Based Transfer Learning: This method emphasizes the identification of connections between the source and target domains and the subsequent transfer of information based on these connections. Markov logic networks (MLNs) are frequently employed in this particular context [26]. According to , Niu et al., 2020 [27] relation-based approaches are rarely utilized.

C. Literature Review

Machine learning methods typically require a significant quantity of labeled data for training, rendering them less feasible in situations where data is scarce or costly to get. Transfer learning overcomes this difficulty by enabling models to apply information acquired from a source domain with ample data to a target domain with little data, consequently improving performance and generalization.

Malmberg Singh et al. 2023, [28] introduced RANSOMNET+, a novel hybrid model that combines convolutional neural networks (CNNs) with pre-trained transformers for ransomware attack classification. RANSOMNET+ delivers exceptional performance by using the advantages of both designs, allowing it to capture complex hierarchical features and local patterns. Their research reveals outstanding efficacy, as RANSOMNET+ attains 99.6% training accuracy, 99.1% testing accuracy, F1 score of 97.64%, recall rate of 98.5% and precision rate of 99.5%. The loss values exhibited remarkable levels of minimalism, varying between 0.0003 and 0.0035 throughout the training and testing phases. RANSOMNET+ outperformed industry-standard ResNet 50 models and state-of-the-art VGG 16 models in terms of F1 score, accuracy, precision, and recall. The interpretability analysis and graphical representations yielded useful insights into the decision-making process of the model. The inclusion of feature distributions, identification of outliers, and analysis of feature relevance improved the model's clarity and practicality. In summary, RANSOMNET+ signifies a notable development in cloud security and the study of ransomware. The exceptional precision and resilience of this technology offer a powerful protection against ransomware assaults on cloud-encrypted data, guaranteeing the security of critical information and maintaining the dependability of cloud storage. This research provides cybersecurity experts and cloud service providers with an effective tool to counteract ransomware threats.

Yoon et al. 2023, [29] introduced a technique that utilizes transfer learning and data augmentation to overcome the constraints of current pedestrian dead reckoning (PDR) systems when it comes to determining distances of moving objects. Their method enables accurate and reliable assessment of the distance of moving objects by employing a little training dataset. Window warping and scaling techniques are used to address the problem of training data being concentrated within a narrow range. The training data consists of accelerometer sensor readings in three axes and pedestrian movement speeds obtained from GPS locations, all gathered via cellphones. The performance evaluation reveals that the distance error performance is high, measuring 3.59 meters. This result is achieved using just around 17% of the training data, which outperforms previous strategies for estimating the distance of moving objects.

Jiang and Durlofsky 2023, [30] introduced a system that use flow-based upscaling to create simplified (low-fidelity) geomodels for most of the training simulations. Their system integrates a transfer learning technique into a recurrent residual U-Net architecture, with network training conducted in three steps. The initial phase, which comprises the majority of the training, utilizes just low-fidelity simulation outcomes. The second and third steps consist of training the output layer and fine-tuning the whole network, respectively, which necessitates a relatively minimal quantity of high-fidelity simulations. The authors establish that by employing 2500 low-fidelity runs and 200 high-fidelity runs, they are able to significantly reduce training simulation costs by 90%. This approach leads to the development of a surrogate model that exhibits similar accuracy to a reference surrogate model trained exclusively on high-fidelity data. The surrogate model is capable of predicting dynamic pressure and saturation fields in new geomodels.

The multi-fidelity surrogate is effectively utilized for history matching using an ensemble-based technique.

Bansal et al. 2023, [31] addressed the persistent problem of obtaining adequate information from pictures to achieve precise categorization through the utilization of deep learning techniques. Their study suggests a methodology that merges deep features derived from the widely-used VGG19 deep convolutional neural network with other handmade feature extraction methods (SIFT, SURF, ORB, and Shi-Tomasi corner detector). The combined characteristics are then categorized using several machine learning classification techniques, including Gaussian Naïve Bayes, Decision Tree, Random Forest, and eXtreme Gradient Boosting. The experiments done on the Caltech-101 benchmark dataset have shown that the Random Forest classifier, when employing the combined features, has an accuracy of 93.73%. This performance surpasses that of other classifiers and approaches. The results indicate that employing a combination of deep learning features and traditional handmade features yields better performance for picture classification tasks compared to depending simply on a single feature extraction method.

Peña-Asensio et al. 2023, [32] devised an automated workflow that employs Convolutional Neural Networks (CNNs) to classify possible meteor detections. This innovative method can detect meteors even in photos that contain stationary objects such as clouds, the Moon, and buildings. In order to accurately ascertain the meteor's position in each frame, the authors employed the Gradient-weighted Class Activation Mapping (Grad-CAM) approach. This technique facilitates the identification of the specific area of interest by merging the activations from the last convolutional layer with the mean gradients throughout the feature map of that layer. Through the integration of these findings with the activation map derived from the initial convolutional layer, the scientists successfully determined the most probable pixel position of the meteor. The model underwent training and evaluation using a substantial dataset collected by the Spanish Meteor Network (SPMN). It attained an accuracy rate of 98%. This novel approach shows potential for decreasing the effort of meteor researchers and station operators while improving the accuracy of meteor tracking and categorization.

Ahmed et al. 2023, [33] developed methods to depict malware signatures as 2D picture representations. They then utilized deep learning techniques to examine the signatures of malware from the BIG15 dataset, which consists of nine different classes. The study assesses the efficacy of several machine learning and deep learning methods in classifying malware. These algorithms include Logistic Regression (LR), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), transfer learning on CNN, and Long Short Term Memory (LSTM). The utilization of the transfer learning technique with InceptionV3 demonstrated favorable outcomes in comparison to other models such as LSTM, attaining accuracy in classification of the train dataset 99.6% and test dataset 98.76%.

Roshni Thanka et al. 2023, [34] discussed the major classifications of skin cancers, which encompass Melanoma, Merkel cell cancer, Squamous cell carcinoma, and Basal cell carcinoma. Melanoma, specifically, presents a notable health risk because of its high occurrence among individuals. Timely identification and anticipation of melanoma can hinder its metastasis, enabling efficacious therapy and remission. The progress in machine learning and deep learning has resulted in the creation of effective computerized diagnostic systems that assist doctors in rapidly anticipating diseases, allowing humans to instantly identify and treat them.Current models either utilize machine learning approaches that are restricted to selecting characteristics or employ deep learning methods that examine features from whole pictures. The suggested method integrates a pre-trained convolutional neural network (VGG16) with machine learning classifiers (such as XGBoost) to perform feature extraction and classification, respectively. This hybrid model significantly improves accuracy, reaching a maximum accuracy of 99.1%, which exceeds the accuracy of other techniques documented in the literature review.

Tiwari et al. 2023, [35] conducted a study that showed the efficacy of a deep learning system in successfully differentiating between various types of hip implants based on radiographs. The DenseNet model demonstrated remarkable accuracy of 99% on this challenge. The study proposes that the utilization of machine learning algorithms can aid in the categorization of hip implants prior to revision surgery, resulting in time savings for surgeons and a decrease in preoperative risks and healthcare costs. This method can furthermore yield crucial data on implant size, allowing surgeons to meticulously and effectively strategize surgical treatments. Moreover, this technology offers the capacity to gather extensive data concerning hip implants, hence facilitating additional advancements in this domain.

Rashid et al. 2022, [36] introduced a novel deep transfer learning method for classifying skin cancer. They utilized MobileNetV2, a deep convolutional neural network designed specifically for differentiating between malignant and benign skin lesions. Their study assessed the effectiveness of the model by analyzing its performance on the ISIC 2020 dataset, which had a notable imbalance in class distribution, with less than 2% of the samples being cancerous. In order to tackle this issue and improve the variety of the dataset, authors implemented several data augmentation approaches. The experimental findings demonstrate that the suggested deep learning approach surpasses existing cutting-edge methods in terms of both accuracy and computing efficiency.

Anaya-Isaza and Mera-Jimenez 2022, [37] conducted a research investigation on the identification of brain tumors utilizing the ResNet50 neural network and a range of data augmentation techniques. The individuals recognized the difficulty of having a restricted amount of information in medical situations and investigated methods to enhance the effectiveness of the model. The authors conducted a comparison between traditional data augmentation strategies and their new method that utilized principal component analysis (PCA). Additionally, they utilized transfer learning from the ImageNet dataset. Their research obtained an outstanding F1 score detection of 92.34% by employing ResNet50 with their technique and transfer learning, so showcasing its efficacy in improving brain tumor detection.

Tseng et al. 2022, [38] suggested applying transfer learning across two machine learning models, EfficientDet-D0 and Faster R-CNN, for the purpose of detecting rice seedlings in paddy fields. This methodology is being contrasted with the conventional method that relies on histograms of oriented gradients (HOG) in conjunction with support vector machine (SVM) classification. The objective is to improve crop yield in order to meet the increasing need for agricultural goods, while reducing the use of resources. This is achieved by employing precision agriculture methods, such as computer vision using pictures obtained from unmanned aerial vehicles (UAVs). Machine learning has demonstrated efficacy in image processing tasks such as classification, detection, and segmentation, rendering it a viable tool for this investigation. The researchers utilize a substantial dataset of UAV photos to train and assess the models, employing performance metrics such as mean average precision (mAP) and mean Intersection-over-Union (mIoU).The findings indicate that the CNN-based models, EfficientDet and Faster R-CNN, surpass the traditional HOG-SVM method in terms of both accuracy and computational efficiency. This highlights the potential of transfer learning in quickly advancing object detection applications with impressive performance metrics. During the training process, EfficientDet attained a mean average precision (mAP) of 95.5% and a mean intersection over union (mIoU) of 67.6%, whereas Faster R-CNN reached almost 99.6% in mIoU and 100% in mAP. During the testing phase, the obtained scores were marginally lower, however still much higher compared to the HOG-SVM technique. In summary, the use of transfer learning greatly expedited the creation of object identification apps, resulting in impressive performance metrics. Specifically, there was a 10% increase in mean average precision (mAP) and mean intersection over union (mIoU) compared to the conventional technique.

Islam et al. 2022, [39] presented a transfer learning (TL) method that employs Convolutional Neural Networks (CNNs). This approach utilizes transfer learning by using four pre-existing deep learning (DL) models—VGG16, ResNet18, DenseNet161, and AlexNet—each equipped with pre-trained weights obtained from ImageNet. The evaluation of these models is conducted based on four fundamental metrics: accuracy, recall, precision, and F1-score. When the suggested technique utilizing AlexNet is applied to the CCIC dataset, it outperforms current models by reaching a testing F1-score of 99.86%, recall of 99.80%, precision of 99.92%, and accuracy of 99.90% specifically for the crack class. In order to further confirm the efficacy of the method, they employ an external dataset (BWCI from Kaggle). The VGG16, ResNet18, DenseNet161, and AlexNet models attain accuracies of 99.90%, 99.60%, 99.80%, and 99.90%, respectively, when evaluated on the BWCI dataset. This approach, which is based on transfer learning and utilizes CNN technology, shows exceptional performance in detecting cracks in concrete buildings and may also be used to other detection tasks.

Mehmood et al. 2022, [40] introduced a highly accurate and computationally efficient model for the quick and precise diagnosis of lung and colon cancers. This model is a viable alternative to existing detection approaches. The study utilized a substantial dataset consisting of 25,000 histopathological pictures. These images were evenly divided between lung and colon tissues and were categorized into 5 classes for the purposes of training and validation. The method employed consisted of fine-tuning a preexisting neural network, namely AlexNet, by modifying four particular layers before to training it on the given dataset. At first, the model demonstrated favorable classification outcomes for the majority of picture categories, but encountered difficulty with one specific category, resulting in an overall accuracy rate of 89%. To tackle this issue, instead of applying picture enhancing algorithms to the whole dataset, a focused approach was utilized. The images from the underperforming class were improved using a simple and effective contrast enhancement approach. The use of this strategy resulted in significant enhancements. The total accuracy increased significantly from 89% to an amazing 98.4%. Crucially, this improvement preserved the model's computational efficiency, guaranteeing its usefulness for real-time diagnostic applications.

Bargshady et al. 2022, [41] emphasized the significant influence of COVID-19 on worldwide health and underlined the necessity of employing deep learning techniques for automated detection methods to effectively manage extensive datasets. The study advocates for the utilization of X-ray imaging to visualize lung disease associated with COVID-19, as a result of the constraints of manual detection techniques. In order to improve the training dataset, the authors suggest utilizing CycleGAN with transfer learning, especially employing semi-supervised CycleGAN (SSA-CycleGAN). The Inception V3 microtransfer learning model was created specifically for the purpose of detecting COVID-19 from X-ray pictures. The findings demonstrate a high level of accuracy and preparedness for testing with further COVID-19 X-ray pictures. However, in order to conduct a more thorough review, it is necessary to get further information on the dataset, training techniques, evaluation metrics, scalability, and real-world applicability.

Saber et al. 2021, [42] introduced an innovative deep learning model that utilizes transfer learning to assist in the automated identification and diagnosis of potential breast cancer locations. The researchers employed two strategies, namely the 80-20 method and cross-validation. Deep learning architectures are purposefully intended to tackle specific challenges, use the insights acquired from addressing one problem to tackle another closely related one. This model utilizes pre-trained convolutional neural network (CNN) architectures, including Inception V3, ResNet50, VGG-19, VGG-16, and Inception-V2 ResNet, to extract features from the Mammary Image Analysis Society (MIAS) dataset. The model's performance was evaluated using six metrics: accuracy, sensitivity, specificity, F-score, and area under the ROC curve (AUC). The experimental findings demonstrate that Transfer Learning (TL) with the VGG16 model is highly successful in detecting Breast Cancer, with AUC, F-score, precision, specificity, sensitivity and overall accuracy of 0.995, 97.66%, 97.35%, 99.13, 97.83, and 98.96 respectively. The 80-20 approach yielded results of 0.993, 98.04%, 98.84%, 98.84%, 98.2%, 97.27%, and 98.87% for the 10-fold cross-validation procedure.

Danso et al. 2021, [43] introduced an approach that integrates transfer learning techniques with ensemble learning algorithms to develop interpretable individualized risk prediction models for dementia. The first models, referred to as source models, are trained and evaluated using a readily accessible data-set (N = 84,856, mean age = 69 years) that includes 14 years of follow-up data. Their objective is to predict the chance of dementia in people. The decision boundaries of the optimal source model are then improved by employing a surrogate dataset from a younger population (n = 473, mean age = 52 years) to construct an extra prediction model known as the target model. The authors employ the elegant additive annotation (SHAP) technique to visually represent risk variables that contribute to prediction at both the population and individual levels. The highest performing source model has an 87% level of geometric accuracy, a 99% level of specificity, and a 76% level of sensitivity. The target model exhibits enhanced performance in several measures compared to the base model. These improvements include a 16.9% increase in geometric accuracy, a 2.7% increase in specificity, a 19.1% increase in sensitivity, and an 11% increase in the area under the receiver. The area under the receiver operating characteristic curve (AUROC) and the rate of learning transfer efficiency is 20.6%. The primary advantages of this approach are the utilization of a substantial sample size to train the source model, the transfer of knowledge, and the application of the model to a distinct dataset from an undiagnosed population for the early detection and prediction of dementia risk. Additionally, this approach allows for the visualization of the interaction between risk factors that influence the prediction.

Khamparia et al. 2021, [44] emphasized the significance of timely identification of breast cancer, as it has a substantial impact on the survival rates of women. Their research centers around the utilization of transfer learning methodologies for the identification of breast cancer. The authors introduce the modified VGG (MVGG) model and utilize it for analyzing both 2D and 3D mammography datasets. The experimental findings demonstrate that the hybrid transfer and learning model, which integrates MVGG and ImageNet, attains a remarkable accuracy rate of 94.3%. By comparison, employing just the MVGG architecture yields an accuracy of 89.8%. This demonstrates that their pre-trained hybrid network exceeds other convolutional neural networks in performance.

Khamparia et al. 2021, [45] introduced a new deep learning framework that utilizes the Internet of Health and Things (IoHT) to classify skin lesions in images of the skin. The system employs transfer learning. Their approach utilizes many pre-trained architectures, including VGG19, Inception V3, ResNet50, and SqueezeNet, to automatically extract features from photos. The extracted characteristics are subsequently inputted into the fully connected layer of the convolutional neural network for the purpose of classifying skin cells as either benign or malignant, employing dense and max pooling processes. In addition, their technology is seamlessly included into the Internet of Healthcare Things (IoHT) architecture, allowing for remote use to aid medical practitioners in the diagnosis and treatment of skin cancer. An assessment of the framework's performance measures revealed that it surpasses other pre-trained architectures in terms of precision, recall, and accuracy for identifying and categorizing skin cancer from photos of skin lesions.

Alzubaidi et al. 2021, [46] introduces a novel transfer learning technique to overcome earlier limitation of transfer learning. It involves training a deep learning model on extensive unlabeled medical image datasets and subsequently transferring this acquired information to train the model on a smaller collection of labeled medical pictures. Furthermore, a novel deep convolutional neural network (DCNN) model is introduced, integrating the latest advancements in this domain. Several studies have been conducted on difficult medical imaging scenarios related to the categorization of skin and breast cancer. The experimentally obtained data demonstrate that this strategy greatly improves the performance of both classification scenarios. The suggested model for classifying skin cancer achieved an F1 score of 89.09% when trained from the beginning, and this score improved to 98.53% when using the proposed transfer learning technique. Furthermore, in the context of breast cancer classification, the model attained an accuracy of 85.29% when trained from the beginning, but this accuracy improved to 97.51% with the suggested method. These findings suggest that the approach is widely applicable to many medical imaging issues, particularly when there is a large amount of unlabeled data and only a small amount of labeled data available. Additionally, it has the potential to improve task performance within the same field. In addition, a pre-trained skin cancer model was utilized to train on photos of the feet's skin in order to categorize them as either normal or abnormal, especially identifying diabetic foot ulcers. The suggested technique demonstrated its adaptability and efficacy across multiple medical imaging tasks, achieving an F1 score of 86.0% when trained from scratch, 96.25% using transfer learning, and 99.25% using dual transfer learning.

Singh et al. 2021, [47] proposed procedures that use transfer learning to address the obstacles associated in classifying histopathology images, particularly when dealing with unbalanced datasets. The researchers utilize the widely-adopted VGG-19 as the fundamental model and include many state-of-the-art strategies to improve the overall performance of the system. They utilize the information acquired from the ImageNet dataset to transfer this knowledge to the target domain, which consists of histopathology pictures. By conducting experiments on a dataset consisting of 277,524 photos, the authors have shown that their suggested framework works better than the existing approaches discussed in the literature. In addition, they offer insights and instructions for performing transfer learning and addressing unbalanced picture categorization using numerical simulations carried out on a supercomputer.

Loey et al. 2021, [48] presented a hybrid model that combines deep learning and classical machine learning techniques for face mask detection. The model consists of two main components: the first component focuses on feature extraction using ResNet50, while the second component addresses classification of face masks using decision trees, support vector machine (SVM), and ensemble algorithms. The study investigates three face mask datasets: the Real-World Masked Face Dataset (RMFD), the Simulated Masked Face Dataset (SMFD), and Tagged Faces in the Wild (LFW). The SVM classifier achieved high test accuracy across the three datasets: 99.64% in RMFD, 99.49% in SMFD, and 100% in LFW.

Behera et al. 2021, [49] presented a new method for non-destructive classification of papaya fruit ripeness state. The study proposes two approaches using machine learning and transfer learning for this classification task and performs a comparative analysis with different machine learning and transfer learning approaches. The experiment includes 300 images of a sample of papaya fruit, with 100 images representing each of the three stages of maturity. The machine-learning method consists of three sets of features and three classifiers with distinct kernel functions. The features used in this system are Local Binary Pattern (LBP), Histogram of Oriented Gradients (HOG), and Gray Level Cooccurrence Matrix (GLCM). The classifiers employed are k-nearest neighbor (KNN), support vector machine (SVM), and Naïve Bayes. In contrast, the transfer learning technique employs seven pre-trained models: ResNet101, ResNet50, ResNet18, VGG19, VGG16, GoogleNet, and AlexNet. The findings indicate that the KNN algorithm, utilizing weighted Histogram of Oriented Gradients (HOG), surpasses other machine learning models with a perfect accuracy rate of 100% and a training time of 0.0995 seconds. Out of the transfer learning-based models, VGG19 demonstrates the highest performance, achieving 100% accuracy. It completes training in 1 minute and 52 seconds, considering the use of early stopping. The utilization of VGG19 in the suggested classification approach, employing transfer learning, attains a 100% accuracy rate, surpassing the previous method by 6%.

Ashraf et al. 2020, [50] introduced an intelligent system that utilizes a region of interest (ROI) to distinguish between melanoma and nevus. This system used a transfer learning strategy. Their approach involves utilizing an enhanced k-means algorithm to extract regions of interest (ROIs) from images. This method aids in the identification of distinctive characteristics, as it exclusively use images that include melanoma cells for training purposes. The system employs a transfer learning model based on convolutional neural networks (CNNs), which is enhanced with data augmentation techniques utilizing region of interest (ROI) photos from the DermIS and DermQuest databases. The results indicate that DermIS achieved an accuracy of 97.9% and DermQuest achieved an accuracy of 97.4%. These accuracies surpass the performance of existing approaches that rely on using entire pictures for classification.

Jignesh Chowdary et al. 2020, [51] focused on the pressing requirement for automated detection of persons who are not using masks in public settings within the COVID-19 epidemic. The authors suggest a transfer learning approach that involves fine-tuning the InceptionV3 deep learning model and training it on the Simulated Masked Face Dataset (SMFD). Image augmentation techniques are utilized to enhance model performance in light of the scarcity of available data. The proposed model has exceptional accuracy, reaching 99.9% during training and 100% during testing, outperforming other recently suggested approaches.

Niu et al. 2020, [52] employed transfer learning methods to construct a resilient model with a small training dataset. They accomplished this by using expertise from known deep networks like AlexNet, DenseNet, and ResNet. A novel field loss function, known as dual dynamic field distance (4D), was created to improve the precision of field distance measurement. This study presents three primary contributions: attaining the highest level of performance on the TrashNet dataset, pioneering the application of transfer learning in rubbish sorting, and improving the effectiveness of transfer learning by the introduction of a unique 4D domain loss function. The researchers applied two transfer learning techniques, DeepCoral and DDC, on the TrashNet dataset. The DeepCoral-ResNet50 model demonstrated superior performance, achieving a test accuracy of up to 96%. The findings of this work are applicable to a wide range of picture classification tasks that extend beyond garbage sorting.

Pavlyuk 2020, [53] investigated the relationship between the techniques employed in video prediction and the forecasting of spatiotemporal traffic patterns. They analyze the similarities in the topologies of video streams and citywide traffic data and explain the connections between the historical development and current status of these approaches. The study confirms the feasibility of utilizing video prediction models for urban traffic prediction by employing a substantial real-world traffic dataset. The transferred techniques encompass spatial filtering with specified kernels, coupled with time series models and spectral graph convolutional artificial neural networks. The efficacy of these transferred models in predicting future traffic patterns is evaluated by comparing them to baseline traffic forecasting models, which include non-spatial time series models and spatially regularized vector autoregression models. The author's conclusion is that the use of video prediction models and algorithms for urban traffic forecasting is successful in terms of accuracy, development, and training efforts. Moreover, the paper examines the difficulties and barriers involved in transferring techniques and proposes prospective avenues for future research.

Best et al. 2020, [54] examined the potential of transfer learning in the context of software engineering. They explored the use of pre-trained models on non-software engineering data to identify Unified Modeling Language (UML) graphs for software. The experimental findings demonstrate a favorable reaction to transfer learning in relation to the size of the sample, despite the fact that the pre-trained model did not receive training examples from the software domain. The authors conduct a comparative analysis of the transferred network with other networks to showcase its benefits across various sizes of training sets. They propose that transfer learning is particularly efficient for custom deep architectures in terms of classification accuracy, particularly when confronted with limited training data. Ultimately, the study indicates that transfer learning, even with models that lack software engineering components, can enable the utilization of pre-existing deep structures without the necessity for adaptation. This technique offers an option for practitioners who want to use deep learning for image-based classification however may not have the expertise or assurance to design their own network topologies.

Abbasi et al. 2020, [55] employed a robust deep learning convolutional neural network (CNN) using a transfer learning methodology. The findings were compared using several machine learning algorithms, such as Bayes, SVM with different kernels, and Decision Tree, using database of MRI cancer . The GoogleNet model underwent training with machine learning classifiers, which extracted a range of features including morphological, entropy-based, texture, SIFT (invariant scale feature transform), and elliptic Fourier descriptors. Performance evaluation involves the computation of many metrics such as sensitivity, specificity, negative predictive value, positive predictive value, receiver operating curve, and false positive rate. The CNN model, namely GoogleNet, demonstrated superior performance when utilizing the transfer learning strategy. Although machine-learning classifiers like Bayes, SVM with RBF-kernel, and Decision Tree have shown favorable outcomes, the emergence of deep learning technology has displayed remarkable achievements.

Xue et al. 2020, [56] proposed an ensemble transfer learning architecture specifically developed for the classification of cervical pathology pictures into well-, moderately, and badly differentiated categories. They initially created transfer-learning models using the Inception-V3, Xception, VGG-16, and Resnet-50 architectures. In order to enhance the accuracy of categorization, they implement a voting-based ETL technique. The algorithm's performance is assessed using a dataset including 307 pictures that have been stained using three different methods of immunohistochemistry: VEGF, HIF, and AQP. The trials yielded an overall accuracy of 97.03% for AQP staining pictures and 98.61% for weakly differentiated VEGF staining images, which were the highest achievable accuracies. Furthermore, they conducted experiments using the Herlev dataset to distinguish between benign cells and malignant cells, attaining an impressive overall accuracy rate of 98.37%.

Cao and Xiang 2020, [57] introduced a method for trash classification and identification that utilizes transfer learning using the InceptionV3 model. Their objective is to optimize the utilization of waste resources, minimize environmental damage, and streamline the process of rubbish sorting for individuals. The approach entails utilizing data augmentation techniques to increase the size of the dataset. This is followed by constructing a convolutional neural network (CNN) using the InceptionV3 model. The neural network parameters are then fine-tuned depending on the training outcomes. The model attains a training accuracy of 99.3% and a testing accuracy of 93.2%. When utilized for real-world picture identification, the model demonstrates excellent performance and a high level of accuracy in recognizing prevalent undesired items. This technique is pragmatic and carries significance as a point of reference for intelligent waste categorization systems.

D. CHALLENGES OF TRANSFER LEARNING

The challenges mentioned in the literature analyzed for this study regarding transfer learning are:

- **Limited Data Availability:** The lack of labeled data, especially in medical imaging tasks, poses an issue in training correct and generalizable models (Saber et al., 2021; Danso et al., 2021; Alzubaidi et al., 2021).
- **Data Imbalance:** Numerous studies emphasize the difficulty of unbalanced datasets, in which specific classes or categories are notably underrepresented, resulting in biased models and diminished performance (Singh et al., 2021).
- **Ethical Considerations:** Certain literary works explore ethical dilemmas associated with bias in datasets, equity in predictions, and privacy issues when using transfer-learning models in practical settings (Khamparia et al., 2021; Best et al., 2020).
- **Model Complexity and Overfitting:** identified as issues that must be overcome to ensure the generalization and resilience of deep learning models (Islam et al., 2022; Khamparia et al., 2021; Ashraf et al., 2020; Jignesh Chowdary et al., 2020).
- **Feature Representation and Selection:** (Islam et al., 2022; Alzubaidi et al., 2021) discussed the difficulties associated with choosing and depicting transferable characteristics across different fields. The major focus is on finding unchanging elements and minimizing noise particular to each field.
- **Domain Adaptation:** refers to the task of transferring information from source domains to target domains that have distinct distributions or

features. This difficulty has been highlighted in several studies, including those by (Singh et al. 2021, Ashraf et al. 2020, and Best et al. 2020).

- **Hardware and Computational Resources:** (Niu et al. 2020) highlighted issues computational complexity of transfer learning models and the requirement for efficient algorithms that can operate on devices with limited resources.
- **Evaluation Metrics and Benchmarking:** (Khamparia et al., 2021; Niu et al., 2020) emphasizes the continued problem of establishing consistent evaluation measures and benchmarks to assess the success of transfer learning.

The challenges face authors of transfer-learning researches reviewed involve an extensive range of issues, including data-related challenges, model complexity, ethical considerations, domain adaptability, feature representation, assessment approaches, and computing limits. It is essential to tackle these problems in order to make progress in the area and create better transfer learning approaches and applications.

Table 1: Comparison Table:

#	Cite	Dataset	Methodology	Pros	Cons	Result
1	Singh et al., [28]	Cloud data	Transfer learning, Deep learning	high precision, recall, and F1 score Exceptional precision and durability in defending against ransomware assaults	limited emphasis on ransomware attacks restricts the potential to apply the findings to other types of cybersecurity threats.	Precision: 99.5%, Recall: 98.5%, F1 score: 97.64%
2	Yoon et al., [29]	Pedestrian	Transfer learning, Data augmentation	Utilizing limited training datasets, high-performance moving object distance estimation is achieved. tackles the asymmetry of data and the absence of clear labeling	Limited mention of issues with real-world deployment or scalability to bigger datasets	Distance error: 3.59 m

				uses smartphone data to locate pedestrians		
3	Jiang and Durlofsky, [30]	Subsurface	Transfer learning	Decreased training simulation expenses significantly - Almost as accurate as reference models using only low-fidelity data. increases the forecast accuracy of subsurface flow.	fine-tune require high fidelity simulations from initially	Nearly as accurate as reference surrogate
4	Bansal et al., [31]	Caltech-101	Transfer learning, Feature extraction	high accuracy achieves with Random Forest classifier combines traditional handcrafted features for image classification and features of deep learning	Limited discussion of the use of models or computational resources in practical situations	93.73% accuracy with Random Forest
5	Peña-Asensio et al., [32]	Meteor	Transfer learning	Fully automated meteor detection pipeline employing CNNs, Accurate meteor localization with Grad-CAM, Meteor detection with	Automating meteor detection and tracking is challenging due to their random nature, various impact geometry, and false positives	Precision: 98%

				great precision	from various sources, including satellites, airplanes, and artificial light sources.	
6	Ahmed et al., [33]	BIG15	Transfer learning	uses transfer learning with InceptionV3 for high classification accuracy, generates 2D malware signature visuals, and performs comparison analysis using multiple machine learning and deep learning models.	The proposed framework requires a high amount of computational operations and a large storage space on the devices	Classification accuracy: 98.76% on test dataset
7	Roshni Thanka et al., [34]	Skin cancer	Transfer learning, Ensemble methods	The model, which combines pre-trained CNN with machine learning classifiers, achieves significant accuracy in detecting melanoma, outperforming current methods in this regard.	While the proposed hybrid approach of VGG16 and XGBoost achieved high accuracy, the study does not extensively discuss the interpretability of the model	Maximum accuracy of 99.1%
8	Tiwari et al., [35]	Hip implants	Transfer learning	A deep learning algorithm classifies hip implant types using	due to the data collection process from only one center,	Accuracy rate: 99%

				radiographs, potentially reducing preoperative complications and healthcare expenses, improving surgical planning and increasing efficiency.	resulting in four implant designs and varying images for each brand, affecting model efficiency.	
9	Rashid et al., [36]	ISIC 2020	Transfer learning, Data augmentation	- Introduces an innovative deep transfer learning model for melanoma classification - Tackles the problem of class imbalance and enhances classification accuracy - Surpasses existing deep learning approaches in terms of performance	lacks information on the generalizability of the proposed model to different datasets or real-world clinical settings.	Outperformed state-of-the-art techniques
10	Anaya-Isaza and Mera-Jimenez, [37]	MRI	Transfer learning, Data augmentation	Achieved a 92.34% F1 detection score in brain tumour detection using ResNet50 transfer learning, enhancing performance through comparative	- Limited discussion on scalability to larger datasets or real-world clinical deployment	F1 score of 92.34%

				analysis of data augmentation techniques.		
11	Tseng et al., [38]	Rice seedling	Transfer learning, Machine learning	Utilized transfer learning from EfficientDet-D0 and Faster R-CNN for crop detection achieved superior accuracy and computation time compared to traditional HOG-SVM method.	Additional validation is needed for accurate crop detection under various environmental conditions, with superior mean Average Precision and mean Intersection over Union compared to HOG-SVM.	Higher mAP and mIoU compared to HOG-SVM
12	Islam et al., [39]	Concrete crack	Transfer learning, Data augmentation	Utilized transfer-learning techniques to improve concrete crack identification accuracy and F1-score, enhancing performance with pre-trained models like VGG16, and verified efficacy on various datasets.	Insufficient exploration of the model's ability to withstand various concrete surface conditions or external variables	Testing accuracy of 99.90% for AlexNet
13	Mehmood et al., [40]	Lung/Colon	Transfer learning, Class selective processing	Accuracy of lung and colon cancer identification was improved from 89% to	The model's generalizability may be limited by its use of a dataset of	Overall accuracy improved from 89% to 98.4%

				98.4% through a contrast enhancement strategy, demonstrating the efficiency and efficacy of the cancer diagnostic process.	25,000 histopathology images divided into 5 classes, which may not fully represent real-world clinical data.	
14	Bargshady et al., [41]	Extensive COVID-19 X-ray and CT Chest Images Dataset	CycleGAN and transfer learning (TL)	explores automated COVID-19 identification using deep learning techniques, efficiently managing large datasets using CycleGAN and transfer learning, and demonstrating high accuracy in X-ray picture visualization.	information provided lacks details on dataset specifications, process description, evaluation criteria, and scalability, necessitating further assessment for practicality and effectiveness, and may require knowledge and computational resources.	mean squared error of 0.27, mean absolute error of 0.16, AUC of 92.2%, and accuracy of 94.2%.
15	Saber et al., [42]	Breast cancer	Transfer learning, Ensemble models	Transfer learning was successfully used to diagnose breast cancer using pre-trained convolutional neural network architectures,	The proposed model's scalability to larger datasets or different imaging modalities is not discussed, potentially limiting its applicability	Accuracy, sensitivity, specificity, precision, F-score, and AUC reported

				achieving high accuracy, sensitivity, specificity, precision, F-score, and AUC.	in diverse clinical settings.	
16	Danso et al., [43]	Dementia	Transfer learning, Ensemble learning	A model for predicting individualized dementia risk using transfer-learning techniques improved accuracy, sensitivity, specificity, and AUC, using the Integrated SHAP method for explain ability and visualization.	study's inability to directly compare the performance of two modelling approaches on the same dataset may hinder the interpretation of relative differences in feature rankings.	Geometric accuracy of 87%, sensitivity of 76%, specificity of 99%
17	Khampari a et al., [44]	Mammograp hy	Transfer learning	A novel hybrid transfer-learning model for breast cancer detection achieved superior accuracy compared to other convolutional neural network architectures, enhancing radiologists' efficiency in mammogram analysis.	More testing is needed on bigger and more diversified datasets of mammograph y.	Accuracy: 94.3% using hybrid pre-trained network

18	Khampari a et al., [45]	Skin images	Deep Learning	- Developed an IoHT-driven framework for skin cancer classification using transfer learning - Outperformed other pre-trained architectures in terms of performance metrics - Integrated IoHT for remote diagnosis and treatment assistance	Challenges in identifying and diagnosing different skin lesions due to similarities in colour skin imaging	Outperformed other models in evaluation
19	Alzubaidi et al., [46]	Medical images	Deep Learning	using pre-trained CNN architectures, achieving high accuracy, sensitivity, specificity, precision, F-score, and AUC, demonstrating its efficacy in model performance.	Lack of sufficient data for training deep learning models in medical image analysis. Mismatch in learned features between natural images and medical images	Significant improvement in performance
20	Singh et al., [47]	Histopathological images	Deep Learning	A transfer-learning framework has been proposed to address unbalanced picture classification,	Existing datasets are imbalance, No exact solution found for accurate breast cancer detection	Superior performance than existing methods

				using VGG-19 as the basis model and advanced techniques, demonstrating exceptional performance on a large dataset.		
21	Loey et al., [48]	Face mask datasets(RMFD, SMFD,LFW)	Deep Learning, Machine Learning	Developed a hybrid model combining deep learning and machine learning techniques to recognize face masks, achieving exceptional accuracy on multiple datasets during the COVID-19 pandemic.	- Insufficient discourse around the issues of scalability and practical implementation obstacles	High testing accuracy in different datasets
22	Behera et al., [49]	Papaya fruit images	Machine Learning, Transfer Learning	machine learning and transfer learning methodologies for categorizing papaya maturity, achieving 100% accuracy using VGG19 and weighted KNN algorithms	lacked discussion on model capabilities for larger datasets and external validation.	100% accuracy with proposed approach
23	Ashraf et al., [50]	DermIS and DermQuest datasets	Deep Learning	The transfer learning method for melanoma	The sample images for training have class	High accuracy in melanoma detection

				diagnosis, based on ROI, achieved exceptional accuracy on DermIS and DermQuest datasets, addressing a challenging skin cancer detection issue.	imbalance issues.	
24	Jignesh Chowdary et al., [51]	Simulated Masked Face Dataset	Deep Learning	A transfer learning model was developed to automatically recognize face masks, achieving high accuracy in training and testing, addressing a critical health issue using InceptionV3.	Government norms restrict sample size due to security and privacy concerns, making deep learning models struggle to learn in limited samples.	High accuracy during training and testing
25	Niu et al., [52]	DDC, DeepCoral, TrashNet	Deep Learning, Transfer Learning	Transfer learning techniques were used to improve trash-sorting performance on the TrashNet dataset, but the potential for scalability and application to other datasets was not explored.	lacks comprehensive exploration of the scalability of trash sorting activities or the applicability of the findings across various datasets.	Best performance on TrashNet dataset
26	Pavlyuk, [53]	Real-world traffic data	Deep Learning,	study explored	lacked practical	Effective forecasting

		set	Transfer Learning	video prediction models for urban traffic prediction, verified their effectiveness using real-world traffic datasets, and developed novel methodologies,	exploration of practical obstacles.	performance
27	Best et al., [54]	Software UML diagrams	Deep Learning, Transfer Learning	Study explores the use of transfer learning for categorizing software UML diagrams using pre-trained models, demonstrating its effectiveness on software engineering artefacts and offering a substitute for customized deep architectures.	- Limited discussion on the scalability to other software artifact types or external validation	Positive reaction to transfer learning
28	Abbasi et al., [55]	Cancer MRI database	Deep Learning, Transfer Learning	Proposed a transfer-learning framework for unbalanced image classification, using VGG-19 as the foundation and advanced	study lacks sufficient exploration of the applicability of the method to other classes of imbalanced datasets	Outstanding results with deep learning

				techniques, demonstrating exceptional performance on a large dataset.		
29	Xue et al., [56]	Cervical histopathology images	Ensembled Transfer Learning (ETL)	combines Transfer Learning and Ensemble Learning, examining differentiation phases and performance evaluation using weighted voting, and assessing immunohistochemistry techniques using a dataset.	The 307-image dataset for deep learning models raises concerns about overfitting and generalizability, and the computational complexity of training and inference, requiring substantial resources.	Highest overall accuracy of 97.03% on AQP staining images and 98.61% on poor differentiation of VEGF staining images.
30	Cao and Xiang, [57]	Garbage images	Transfer Learning (TL)	The InceptionV3 model achieves 99.3% training and 93.2% test accuracy in rubbish categorization, demonstrating proficiency in recognizing waste objects in photographs, despite dataset limitations.	The model's generalizability and applicability are affected by the dataset's size and scalability, and its 99.3% training accuracy may suggest potential overfitting.	The model exhibits high accuracy in identifying common garbage items, with a training accuracy of 99.3% and a test accuracy of 93.2%.

E. DISCUSSION

This study explores the efficacy of transfer learning across several domains and datasets, emphasizing its influence on enhancing model performance. Data augmentation approaches have a crucial role in improving accuracy, especially in situations when there is a shortage of training data. This has been seen in several studies, such as those focusing on pedestrian recognition, concrete fracture detection, and meteor detection. Deep learning architectures, such as Convolutional Neural Networks (CNNs) and its variations like InceptionV3, ResNet, and VGG, are essential for obtaining high accuracy in applications like melanoma diagnosis, facemask identification, and breast cancer categorization. The efficacy of hybrid models and ensemble approaches in enhancing model resilience and overall performance is apparent, particularly in tasks such as ransomware detection, skin cancer categorization, and dementia risk prediction. Issues like as the quantity of the dataset, imbalances in class distribution, and limitations in computational resources are recognized as factors that affect the interpretation and practicality of the results in real-world scenarios. Conducting a comparative examination of performance indicators including as accuracy, precision, recall, F1 score, and classification rates provides valuable insights into the strengths and limitations seen in various tasks and domains. Proposed future research areas focus on innovative approaches and emerging trends in transfer learning, deep learning, and machine learning. The aim is to improve model performance and applicability.

The results of the assessed research illustrate the effectiveness and adaptability of transfer learning strategies in improving model performance and tackling issues particular to different domains. Transfer learning consistently demonstrated substantial enhancements in accuracy, precision, recall, F1 score, and other performance. metrics across various domains including cloud data analysis, pedestrian localization, subsurface flow modeling, image classification, anomaly detection, and medical diagnostics. Transfer learning techniques consistently demonstrated excellent accuracy rates, ranging from 93.73% to 100%, across many datasets and applications. Prominent instances encompass malware categorization with an accuracy rate of 99.6%, face mask identification with a range of 99.64% to 100%, and breast cancer diagnosis with a precision of 98.96%.

Multiple studies have documented remarkable levels of accuracy, recall, and F1 scores, which demonstrate the strength and reliability of transfer learning models. For example, the precision rates in detecting ransomware attacks reached as high as 99.5%, while the recall rates varied from 76% to 98.5% in different applications such as brain tumor detection, skin cancer classification, and lung/colon malignancy detection. Transfer learning demonstrated exceptional performance in some applications, including COVID-19 detection with an accuracy of 94.2%, concrete fracture detection with a testing accuracy of 99.90%, and face mask recognition with a training accuracy of 99.9% and a testing accuracy of 100%.

F. Conclusion and Future Direction

This paper highlights the significant influence of transfer learning in improving the performance of models across various domains and datasets. Transfer learning is most useful in situations when there is a little amount of training data. In these cases, data augmentation techniques play a vital role in enhancing accuracy. Deep learning architectures, particularly convolutional neural network (CNN) variations such as InceptionV3, ResNet, and VGG, are essential for obtaining high accuracy in diverse tasks including melanoma detection, facemask identification, and breast cancer categorization. The use of hybrid models and ensemble approaches boosts the resilience and overall effectiveness of models, as seen in tasks such as detecting ransomware, classifying skin cancer, and predicting the risk of dementia. Nevertheless, it is necessary to tackle obstacles like as the magnitude of the dataset, the uneven distribution of classes, and the availability of computing resources in order to guarantee the comprehensibility and practicality of the outcomes. An examination of performance indicators allows for significant insights into the strengths and limitations of transfer learning across various activities and domains. Future research should prioritize the development of innovative approaches and investigation of emerging trends in transfer learning, deep learning, and machine learning. This will lead to continuous improvement in model performance and its suitability for real-world applications.

References

[1] C. Cai et al., "Transfer Learning for Drug Discovery," J. Med. Chem., vol. 63, no. 16, pp. 8683–8694, Aug. 2020, doi: 10.1021/acs.jmedchem.9b02147.

[2] M. S. Azari, F. Flammini, S. Santini, and M. Caporuscio, "A Systematic Literature Review on Transfer Learning for Predictive Maintenance in Industry 4.0," IEEE Access, vol. 11, pp. 12887–12910, 2023, doi: 10.1109/ACCESS.2023.3239784.

[3] P. Yan et al., "A Comprehensive Survey of Deep Transfer Learning for Anomaly Detection in Industrial Time Series: Methods, Applications, and Directions," IEEE Access, vol. 12, pp. 3768–3789, 2024, doi: 10.1109/ACCESS.2023.3349132.

[4] I. H. Sarker, "Machine Learning: Algorithms, Real-World Applications and Research Directions," SN COMPUT. SCI., vol. 2, no. 3, p. 160, Mar. 2021, doi: 10.1007/s42979-021-00592-x.

[5] "Machine Learning Applications based on SVM Classification A Review | Qubahan Academic Journal." Accessed: Apr. 01, 2024. [Online]. Available: https://journal.qubahan.com/index.php/qaj/article/view/50

[6] M. Iman, H. R. Arabnia, and K. Rasheed, "A Review of Deep Transfer Learning and Recent Advancements," Technologies, vol. 11, no. 2, Art. no. 2, Apr. 2023, doi: 10.3390/technologies11020040.

[7] Z. Alyafeai, M. S. AlShaibani, and I. Ahmad, "A Survey on Transfer Learning in Natural Language Processing." arXiv, May 31, 2020. doi: 10.48550/arXiv.2007.04239.

[8] P. Kora et al., "Transfer learning techniques for medical image analysis: A review," Biocybernetics and Biomedical Engineering, vol. 42, no. 1, pp. 79–107, Jan. 2022, doi: 10.1016/j.bbe.2021.11.004.

[9] J. N. Saeed, A. M. Abdulazeez, and D. A. Ibrahim, "2D Facial Images Attractiveness Assessment Based on Transfer Learning of Deep Convolutional Neural Networks," in 2022 4th International Conference on Advanced Science

and Engineering (ICOASE), Sep. 2022, pp. 13–18. doi: 10.1109/ICOASE56293.2022.10075585.
[10] S. Niu, "Data-Efficient Machine Learning With Focus on Transfer Learning," PhD Thesis, Embry-Riddle Aeronautical University, 2021. Accessed: Apr. 01, 2024. [Online]. Available: https://search.proquest.com/openview/e548fcb8d7fcc7dd216e83470636809e/1?pq-origsite=gscholar&cbl=18750&diss=y
[11] C. Janiesch, P. Zschech, and K. Heinrich, "Machine learning and deep learning," Electron Markets, vol. 31, no. 3, pp. 685–695, Sep. 2021, doi: 10.1007/s12525-021-00475-2.
[12] D. Onita, "Active Learning Based on Transfer Learning Techniques for Text Classification," IEEE Access, vol. 11, pp. 28751–28761, 2023, doi: 10.1109/ACCESS.2023.3260771.
[13] H. Li, Z. Ma, and Y. Weng, "A Transfer Learning Framework for Power System Event Identification," IEEE Transactions on Power Systems, vol. 37, no. 6, pp. 4424–4435, Nov. 2022, doi: 10.1109/TPWRS.2022.3153445.
[14] M. Weber, M. Auch, C. Doblander, P. Mandl, and H.-A. Jacobsen, "Transfer learning with time series data: a systematic mapping study," Ieee Access, vol. 9, pp. 165409–165432, 2021.
[15] K. Combs, H. Lu, and T. Bihl, "Transfer Learning and Analogical Inference: A Critical Comparison of Algorithms, Methods, and Applications," Algorithms, vol. 16, p. 146, Mar. 2023, doi: 10.3390/a16030146.
[16] F. Zhuang et al., "A comprehensive survey on transfer learning," Proceedings of the IEEE, vol. 109, no. 1, pp. 43–76, 2020.
[17] S. Bozinovski, "Reminder of the First Paper on Transfer Learning in Neural Networks, 1976," Informatica, vol. 44, no. 3, Art. no. 3, Sep. 2020, doi: 10.31449/inf.v44i3.2828.
[18] Y. Jang, H. Lee, S. J. Hwang, and J. Shin, "Learning What and Where to Transfer." arXiv, May 14, 2019. doi: 10.48550/arXiv.1905.05901.
[19] Y. Zhou, X. Zhang, Y. Wang, and B. Zhang, "Transfer learning and its application research," Journal of Physics: Conference Series, vol. 1920, p. 012058, May 2021, doi: 10.1088/1742-6596/1920/1/012058.
[20] S. Kawish, H. Louafi, and Y. Yao, "An Instance-based Transfer Learning Approach, Applied to Intrusion Detection," in 2023 20th Annual International Conference on Privacy, Security and Trust (PST), Aug. 2023, pp. 1–7. doi: 10.1109/PST58708.2023.10319986.
[21] D. Wang, X. Chen, and D. Chen, "DDoS Detection Method Based on Instance Transfer Learning," in 2021 IEEE 6th International Conference on Signal and Image Processing (ICSIP), Oct. 2021, pp. 1053–1058. doi: 10.1109/ICSIP52628.2021.9688784.
[22] S. Elmi and K.-L. Tan, "Travel Time Prediction in Missing Data Areas: Feature-based Transfer Learning Approach," in 2020 IEEE 22nd International Conference on High Performance Computing and Communications; IEEE 18th International Conference on Smart City; IEEE 6th International Conference on Data Science and Systems (HPCC/SmartCity/DSS), Dec. 2020, pp. 1088–1095. doi: 10.1109/HPCC-SmartCity-DSS50907.2020.00196.

[23] C. H. Mendigoria, H. Aquino, R. Concepcion, O. J. Alajas, E. Dadios, and E. Sybingco, “Vision-based Postharvest Analysis of Musa Acuminata Using Feature-based Machine Learning and Deep Transfer Networks,” in 2021 IEEE 9th Region 10 Humanitarian Technology Conference (R10-HTC), Sep. 2021, pp. 01–06. doi: 10.1109/R10-HTC53172.2021.9641575.
[24] W. Wang and B. Li, “A novel model based on a 1D-ResCNN and transfer learning for processing EEG attenuation,” Computer Methods in Biomechanics and Biomedical Engineering, vol. 26, no. 16, pp. 1980–1993, Dec. 2023, doi: 10.1080/10255842.2022.2162339.
[25] X. Shan, Y. Lu, Q. Li, and Y. Wen, “Model-Based Transfer Learning and Sparse Coding for Partial Face Recognition,” IEEE Transactions on Circuits and Systems for Video Technology, vol. 31, no. 11, pp. 4347–4356, Nov. 2021, doi: 10.1109/TCSVT.2020.3047140.
[26] M. Wang and H. Yang, “Research on Personal Credit Risk Assessment Model Based on Instance-Based Transfer Learning,” IJIS, vol. 11, no. 01, pp. 44–55, 2021, doi: 10.4236/ijis.2021.111004.
[27] S. Niu, Y. Liu, J. Wang, and H. Song, “A decade survey of transfer learning (2010–2020),” IEEE Transactions on Artificial Intelligence, vol. 1, no. 2, pp. 151–166, 2020.
[28] A. Singh, Z. Mushtaq, H. A. Abosaq, S. N. F. Mursal, M. Irfan, and G. Nowakowski, “Enhancing Ransomware Attack Detection Using Transfer Learning and Deep Learning Ensemble Models on Cloud-Encrypted Data,” Electronics, vol. 12, no. 18, p. 3899, Sep. 2023, doi: 10.3390/electronics12183899.
[29] J. Yoon, J. Oh, and S. Kim, “Transfer Learning Approach for Indoor Localization with Small Datasets,” Remote Sensing, vol. 15, no. 8, p. 2122, Apr. 2023, doi: 10.3390/rs15082122.
[30] S. Jiang and L. J. Durlofsky, “Use of Multifidelity Training Data and Transfer Learning for Efficient Construction of Subsurface Flow Surrogate Models,” Journal of Computational Physics, vol. 474, p. 111800, Feb. 2023, doi: 10.1016/j.jcp.2022.111800.
[31] M. Bansal, M. Kumar, M. Sachdeva, and A. Mittal, “Transfer learning for image classification using VGG19: Caltech-101 image data set,” J Ambient Intell Human Comput, vol. 14, no. 4, pp. 3609–3620, Apr. 2023, doi: 10.1007/s12652-021-03488-z.
[32] E. Peña-Asensio, J. M. Trigo-Rodríguez, P. Grèbol-Tomàs, D. Regordosa-Avellana, and A. Rimola, “Deep machine learning for meteor monitoring: Advances with transfer learning and gradient-weighted class activation mapping,” Planetary and Space Science, vol. 238, p. 105802, Nov. 2023, doi: 10.1016/j.pss.2023.105802.
[33] M. Ahmed, N. Afreen, M. Ahmed, M. Sameer, and J. Ahamed, “An inception V3 approach for malware classification using machine learning and transfer learning,” International Journal of Intelligent Networks, vol. 4, pp. 11–18, Jan. 2023, doi: 10.1016/j.ijin.2022.11.005.
[34] M. Roshni Thanka et al., “A hybrid approach for melanoma classification using ensemble machine learning techniques with deep transfer learning,”

Computer Methods and Programs in Biomedicine Update, vol. 3, p. 100103, Jan. 2023, doi: 10.1016/j.cmpbup.2023.100103.

[35] A. Tiwari, A. K. Yadav, K. S. Akshay, and V. Bagaria, "Evaluation of machine learning models to identify hip arthroplasty implants using transfer learning algorithms," Journal of Clinical Orthopaedics and Trauma, vol. 47, p. 102312, Dec. 2023, doi: 10.1016/j.jcot.2023.102312.

[36] J. Rashid et al., "Skin Cancer Disease Detection Using Transfer Learning Technique," Applied Sciences, vol. 12, no. 11, Art. no. 11, Jan. 2022, doi: 10.3390/app12115714.

[37] A. Anaya-Isaza and L. Mera-Jimenez, "Data Augmentation and Transfer Learning for Brain Tumor Detection in Magnetic Resonance Imaging," IEEE Access, vol. 10, pp. 23217–23233, 2022, doi: 10.1109/ACCESS.2022.3154061.

[38] H.-H. Tseng, M.-D. Yang, R. Saminathan, Y.-C. Hsu, C.-Y. Yang, and D.-H. Wu, "Rice Seedling Detection in UAV Images Using Transfer Learning and Machine Learning," Remote Sensing, vol. 14, no. 12, Art. no. 12, Jan. 2022, doi: 10.3390/rs14122837.

[39] M. M. Islam, M. B. Hossain, M. N. Akhtar, M. A. Moni, and K. F. Hasan, "CNN Based on Transfer Learning Models Using Data Augmentation and Transformation for Detection of Concrete Crack," Algorithms, vol. 15, no. 8, Art. no. 8, Aug. 2022, doi: 10.3390/a15080287.

[40] S. Mehmood et al., "Malignancy Detection in Lung and Colon Histopathology Images Using Transfer Learning With Class Selective Image Processing," IEEE Access, vol. 10, pp. 25657–25668, 2022, doi: 10.1109/ACCESS.2022.3150924.

[41] G. Bargshady, X. Zhou, P. D. Barua, R. Gururajan, Y. Li, and U. R. Acharya, "Application of CycleGAN and transfer learning techniques for automated detection of COVID-19 using X-ray images," Pattern Recognit Lett, vol. 153, pp. 67–74, Jan. 2022, doi: 10.1016/j.patrec.2021.11.020.

[42] A. Saber, M. Sakr, O. Abo-Seida, A. Keshk, and H. Chen, "A Novel Deep-Learning Model for Automatic Detection and Classification of Breast Cancer Using the Transfer-Learning Technique," IEEE Access, vol. PP, pp. 1–1, May 2021, doi: 10.1109/ACCESS.2021.3079204.

[43] S. O. Danso, Z. Zeng, G. Muniz-Terrera, and C. W. Ritchie, "Developing an Explainable Machine Learning-Based Personalised Dementia Risk Prediction Model: A Transfer Learning Approach With Ensemble Learning Algorithms," Front Big Data, vol. 4, p. 613047, 2021, doi: 10.3389/fdata.2021.613047.

[44] A. Khamparia et al., "Diagnosis of breast cancer based on modern mammography using hybrid transfer learning," Multidim Syst Sign Process, vol. 32, no. 2, pp. 747–765, Apr. 2021, doi: 10.1007/s11045-020-00756-7.

[45] A. Khamparia, P. K. Singh, P. Rani, D. Samanta, A. Khanna, and B. Bhushan, "An internet of health things-driven deep learning framework for detection and classification of skin cancer using transfer learning," Transactions on Emerging Telecommunications Technologies, vol. 32, no. 7, p. e3963, 2021, doi: 10.1002/ett.3963.

[46] L. Alzubaidi et al., "Novel Transfer Learning Approach for Medical Imaging with Limited Labeled Data," Cancers (Basel), vol. 13, no. 7, p. 1590, Mar. 2021, doi: 10.3390/cancers13071590.

[47] R. Singh, T. Ahmed, A. Kumar, A. K. Singh, A. K. Pandey, and S. K. Singh, “Imbalanced Breast Cancer Classification Using Transfer Learning,” IEEE/ACM Trans Comput Biol Bioinform, vol. 18, no. 1, pp. 83–93, 2021, doi: 10.1109/TCBB.2020.2980831.
[48] M. Loey, G. Manogaran, M. H. N. Taha, and N. E. M. Khalifa, “A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic,” Measurement, vol. 167, p. 108288, Jan. 2021, doi: 10.1016/j.measurement.2020.108288.
[49] S. K. Behera, A. K. Rath, and P. K. Sethy, “Maturity status classification of papaya fruits based on machine learning and transfer learning approach,” Information Processing in Agriculture, vol. 8, no. 2, pp. 244–250, Jun. 2021, doi: 10.1016/j.inpa.2020.05.003.
[50] R. Ashraf et al., “Region-of-Interest Based Transfer Learning Assisted Framework for Skin Cancer Detection,” IEEE Access, vol. 8, pp. 147858–147871, 2020, doi: 10.1109/ACCESS.2020.3014701.
[51] G. Jignesh Chowdary, N. S. Punn, S. K. Sonbhadra, and S. Agarwal, “Face Mask Detection Using Transfer Learning of InceptionV3,” in Big Data Analytics, L. Bellatreche, V. Goyal, H. Fujita, A. Mondal, and P. K. Reddy, Eds., Cham: Springer International Publishing, 2020, pp. 81–90. doi: 10.1007/978-3-030-66665-1_6.
[52] S. Niu, J. Wang, Y. Liu, and H. Song, “Transfer Learning based Data-Efficient Machine Learning Enabled Classification,” in 2020 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech), Aug. 2020, pp. 620–626. doi: 10.1109/DASC-PICom-CBDCom-CyberSciTech49142.2020.00108.
[53] Pavlyuk, “Transfer Learning: Video Prediction and Spatiotemporal Urban Traffic Forecasting,” Algorithms, vol. 13, no. 2, p. 39, Feb. 2020, doi: 10.3390/a13020039.
[54] N. Best, J. Ott, and E. J. Linstead, “Exploring the efficacy of transfer learning in mining image-based software artifacts,” Journal of Big Data, vol. 7, no. 1, p. 59, Aug. 2020, doi: 10.1186/s40537-020-00335-4.
[55] A. A. Abbasi et al., “Detecting prostate cancer using deep learning convolution neural network with transfer learning approach,” Cogn Neurodyn, vol. 14, no. 4, pp. 523–533, Aug. 2020, doi: 10.1007/s11571-020-09587-5.
[56] D. Xue et al., “An Application of Transfer Learning and Ensemble Learning Techniques for Cervical Histopathology Image Classification,” IEEE Access, vol. PP, pp. 1–1, Jun. 2020, doi: 10.1109/ACCESS.2020.2999816.
[57] L. Cao and W. Xiang, Application of Convolutional Neural Network Based on Transfer Learning for Garbage Classification. 2020, p. 1036. doi: 10.1109/ITOEC49072.2020.9141699.