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A Hybrid Deep Learning Framework using Transfer Learning as the Feature Extractor in Environmental Health Risk Prediction

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***Abstract*— Transfer learning is a promising machine learning paradigm that has demonstrated superior performance compared to conventional classifiers and plays a central role in computer vision and natural language applications. It enables models to learn general knowledge from a source domain and fine-tune it for specific tasks in a target domain. However, its practical application is limited in data-starved scenarios, where the target model's training data is scarce. In such cases, feature construction may lack precision due to the small size of the training dataset, and the transformed source data may be insufficient to construct an accurate classifier for the target domain. In this work, we propose a hybrid deep learning (HDL) framework that utilizes a neural network-based feature extractor trained with traditional transfer learning and then trains conventional classifiers with the extracted features. This approach addresses the data scarcity problem in medical applications and improves the model's ability to predict rare health events. Through this hybrid deep learning method, new features are learned via knowledge transfer, and these fine-tuned features enhance the performance of conventional classifiers. We design several transfer learning architectures that facilitate this HDL approach and provide an in-depth analysis of model performance. Extensive experiments on data from 23 asthma patients for individual asthma risk prediction models demonstrate the effectiveness of the proposed HDL framework compared to five existing conventional classifiers and a traditional transfer learning model. The improvement in sensitivity ranges from 45.31% to 136.16% for conventional classifiers and from 30.65% to 42.44% for the traditional transfer learning model.**

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***Index Terms*— transfer learning, deep learning, feature extraction, data starved contexts, rare health event**

I. Introduction

Numerous machine learning (ML) algorithms have been proposed for preventive health management, such as health risk prediction, disease diagnostics and care assessment [1], [2]. However, developing individual-based prediction models that accurately predict rare health events remains a significant challenge. This difficulty arises due to class imbalances in the data and the limited availability of high-quality labeled datasets, especially at the individual patient level. Despite these challenges, medical applications still rely heavily on classical ML algorithms.

Many research groups have proposed various techniques to address these data limitations, including synthetic minority oversampling techniques (SMOTEs) [3]–[7], generative adversarial networks (GANs) [8], autoencoders [9]–[15], and meta-algorithmic approaches [16]. However, such data-level approaches have shown limitations in improving classifier performance, particularly in data-starved contexts common in medical applications where there are few daily observations per patient [17]. In our study of asthma risk prediction, the average dataset size of a patient's data set is 168 records, making synthetic data generation alone insufficient for constructing deep learning models.

This paper addresses the challenge of limited training data by developing a novel deep learning framework that helps classifiers overcome the issue of data scarcity. Transfer Learning (TL) is a commonly used technique to deal with limited high-quality labeled data, but the very small size of training data significantly limits the improvements in individual-based health risk modeling achievable with traditional TL. We propose a hybrid deep learning (HDL) framework that uses a neural network (NN) pre-trained with TL as a feature extractor, combined with traditional classification models that are less data-hungry. This approach allows us to develop more accurate and robust classifiers using limited training data.

Deep neural networks (DNNs) have achieved significant advancements in various applications, particularly in computer vision and natural language processing [18]–[21]. Recent developments in DNN architectures have also shown promise in creating highly accurate prediction models for tabular data, which is ubiquitous in medical applications [22]–[24].

However, DNNs require vast amounts of data to train models that generalize well and perform effectively on unseen data. As a result, their performance is significantly compromised when training on small datasets, leading to unsatisfactory accuracy in risk analysis for rare health events [1], [2], [25]. This limitation is particularly problematic in health prediction modeling, where misclassifying a "rare" event can have critical consequences.

On the other hand, the structure of DNNs provides an efficient mechanism for applying TL, which transfers knowledge from a source domain with sufficient labeled data to a target domain with smaller datasets [26]. With their end-to-end differentiable structure and ability to extract complex data representations, traditional DNN architectures enable the transfer of representations learned from large pre-training datasets. In the TL paradigm, DNNs trained on large population data are then fine-tuned on individual patient data, which often consists of much smaller datasets. However, since the target model is still a neural network, it tends to require a substantial amount of training data during the retraining step. This raises a key research question: how can efficient knowledge transfer be achieved with limited data in medical applications? Common strategies for reducing the data requirements of the target model include modifying the source model's architecture before retraining and adjusting the level of fitting with regularization techniques such as dropout. In this paper, we propose using the output from a middle layer of the source model as input to a much simpler, and therefore less data-hungry, target model such as a decision tree or support vector machine. This question was presented in our earlier work and we tacked it in this study [27].

On the other hand, the structure of DNNs provides an efficient mechanism for applying TL, which transfers knowledge from a source domain with sufficient labeled data to a target domain with smaller datasets [26]. With their end-to-end differentiable structure and ability to extract complex data representations, traditional DNN architectures enable the transfer of representations learned from large pre-training datasets. In the TL paradigm, DNNs trained on large population data are then fine-tuned on individual patient data, which often consists of much smaller datasets. However, since the target model is still a neural network, it tends to require a substantial amount of training data during the retraining step. This raises a key research question: how can efficient knowledge transfer be achieved with limited data in medical applications? Common strategies for reducing the data requirements of the target model include modifying the source model's architecture before retraining and adjusting the level of fitting with regularization techniques such as dropout. In this paper, we propose using the output from a middle layer of the source model as input to a much simpler, and therefore less data-hungry, target model such as a decision tree or support vector machine. We previously posed this question in our earlier work [27] and present the solution in this follow-up study .

Our primary focus is on architectural solutions that combine the TL paradigm with conventional classification algorithms. We demonstrate that significant improvements in accuracy can be achieved using this framework in medical applications that are severely data-starved — the characteristic that limits the effectiveness of traditional TL techniques. Our secondary focus is to identify patterns related to the feature extractor, such as model architecture, fine-tuning TL strategies, and the number of training samples, to provide valuable insights for future research on this hybrid deep learning framework. Our third objective is to evaluate the robustness of the proposed framework by implementing various TL architectures with five selected conventional classification algorithms: decision trees, k-nearest neighbors, logistic regression, Naive Bayes, and support vector machines. Results from extensive experiments on 23 asthma patients' datasets demonstrate that the proposed approach is robust across conventional classification algorithms and has the potential to significantly improve the performance of models for predicting adverse asthmatic health events. Although this paper presents a medical application, the proposed framework is applicable to a wide range of data-starved contexts.

The remainder of the paper is organized as follows: Section II provides an in-depth review of the relevant literature, focusing on transfer learning approaches for tabular data. In Section III, we introduce a novel hybrid deep learning framework that incorporates transfer learning. Section IV details the evaluation of our proposed models using datasets from asthma patients and presents the corresponding experimental results. Section V provides an analysis of our findings, highlighting their significance as a contribution to environmental health risk prediction. Finally, Section VI concludes the paper and outlines potential future research directions.

II. Background

Our proposed HDL framework is mainly related to the following topics in machine learning: TL general use, TL use in tabular data, TL as feature extractor, deep learning for TL, and TL in medical applications. In this section, we review related work in these topics.

TL enables researchers to take advantage of large high quality labeled datasets in related source domains to reduce the need for as much domain-specific data [28]. It is therefore an option for constructing classifiers with a large amount of non-specific general data but a smaller amount of specialized data. TL has been shown to significantly improve the accuracy of the models in computer vision and natural language processing [26], [29], [30]. Some notable works proposed TL as the pre-trained feature extractor incorporated into the complex pipelines of successful object detection and semantic segmentation models [31], [32].

A common goal of deep learning techniques applied to transfer learning is to extract high-level features through hierarchical structures that capture variations across domains [33], [34]. In homogeneous TL, the main goal is to improve model generalization across different domains within the same feature space, with effective feature representation being crucial for success [26], [35]. The Structural Correspondence Learning algorithm proposed in [36] uses "pivot" features to bridge domains and reduce differences. Several dimensionality

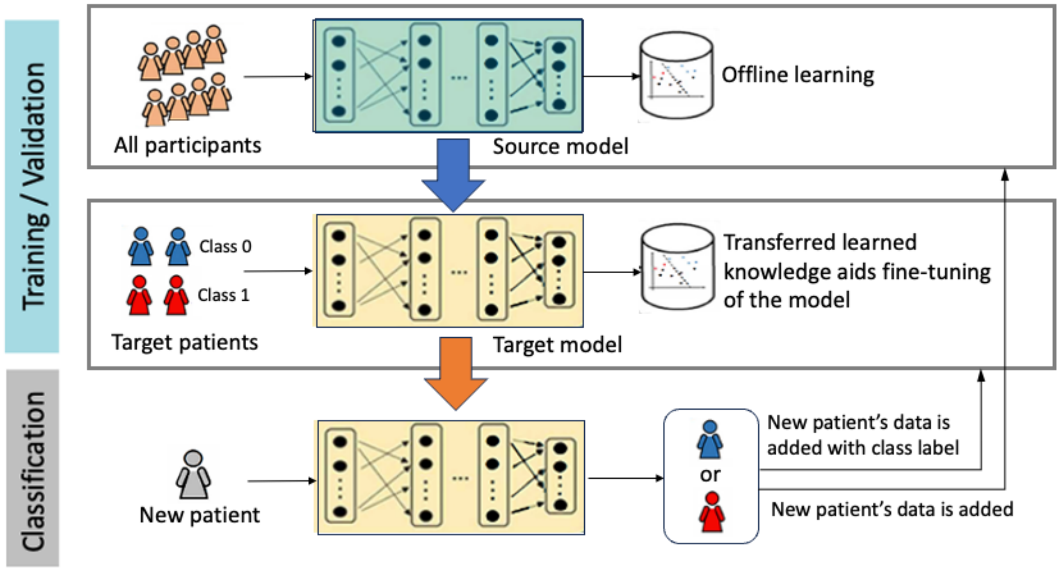


Fig. 1: An overview of transfer learning in health domain

reduction methods based on Hilbert space embedding have been proposed to minimize domain gaps while preserving key data properties, such as variance and structure [37], [38]. Another approach proposed in [39] involves a simple mapping function that augments features from both domains in a high-dimensional space. Its extensions, using semi-supervised learning, incorporate unlabeled target domain data to enhance learning.

Authors in [40] proposed a self-taught learning framework based on sparse coding [41] that learns features from large-scale unlabeled data. Another approach, developed in [42] uses stack denoised autoencoders (SDA) to learn invariant features for cross-domain sentiment classification. Results extending that work present a variation of SDA that offer improved efficiency [43]. Studies presented in [44], [45] explored reusing high-level features from deep neural networks trained on large datasets for target tasks. While many approaches have seen success in image processing, it remains unclear whether transfer learning as a feature extractor can significantly improve classifier performance for predicting rare health events in tabular data, achieving higher classification accuracy compared to directly using the new classification layer of the fine-tuned model (target model) for classification. This paper focuses on learning precise feature mappings for homogeneous features when target training data is limited.

While TL has shown great promise in medical image classification with limited data availability such as the context of image analysis of MRI or CT scan data [46]–[50], it has not been fully investigated as a robust technique with sparse tabular data particularly in health applications. A recent review paper [51] finds that transfer learning is under explored and that the question of how to perform knowledge transfer in the tabular data remains open. The work in [52] focuses on converting tabular data to images and applying transfer learning with vision models. In our work, we seek to find a solution to health risk prediction by applying the transfer learning paradigm to combine conventional classification algorithms that can be trained on fairly limited datasets with recent successful deep learning models for tabular data.

Some studies have used ML techniques for the prediction of asthma exacerbation, including alarm systems, proposed in [53]; predictions of control deterioration in [54]; feature extraction for risk detection in [55]; machine learning frameworks for risk prediction in [56] and conventional transfer learning models for the prediction of individual patients' risk [27], [57]. Figure 1 shows an example of the traditional TL framework applied in health domain, where the source model is trained using a vast size of public data and it is then retrained for the target model using targeted patients. The fine-tuned model predicts the class of health condition for a new patient. The data of the new patient is added to source and target data. In our study, we took the general approach to TL but our individual-level modeling using small training data requires new architectural solutions to achieve the model accuracy.

III. Methodology

To study hybrid deep learning utilizing transfer learning, we need to define a target for prediction and select benchmark tasks and training pipelines. This section presents the definition of health risk, the proposed HDL framework, architectural designs of TL and its implementation.

A. Health Risk Definition

One common indicator of asthma symptoms is peak expiratory flow rate (PEFR). To assess the severity or exacerbation of asthma, population-level data is often used to define green, yellow, and red zones based on standardized "normal" values, which consider factors like gender, age, and height [58]. However, due to the variability in baseline PEFR among individuals, using standardized data may lead to false

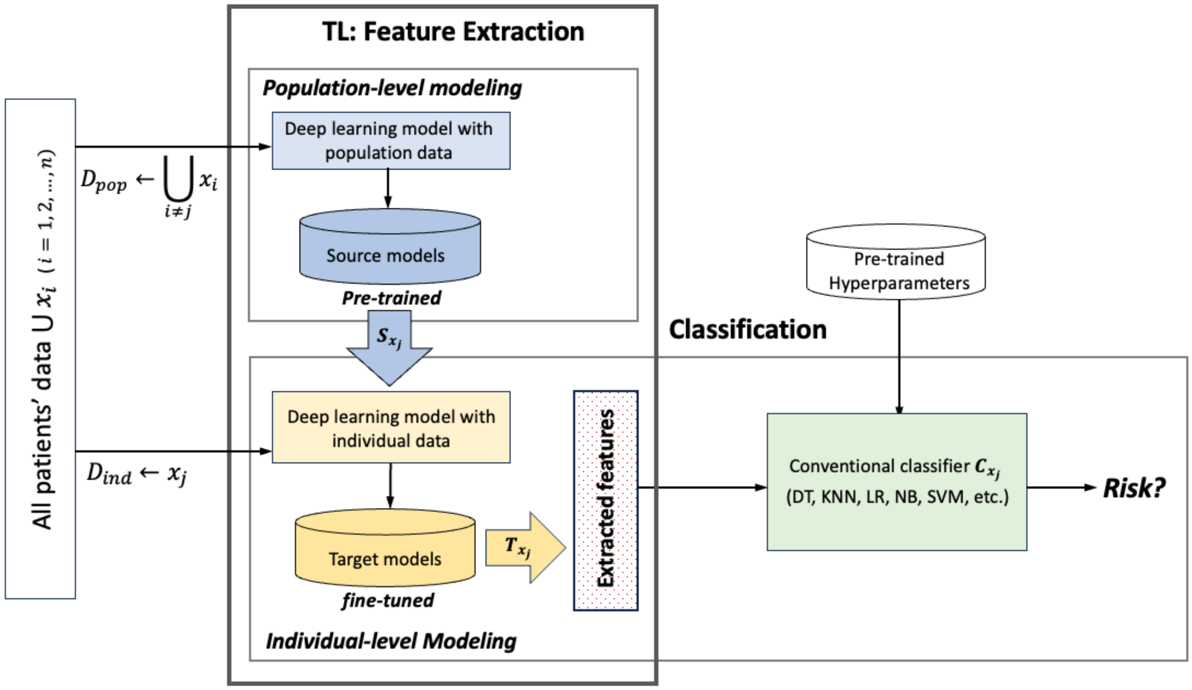


Fig. 2: Workflow of the Hybrid Deep Learning framework.

positives or negatives. Instead, patient-specific clusters can be used to personalize risk zones for individual patients. In this study, we apply a simplified version of an individual-specific exacerbation zoning method from [56], which classifies a patient's asthma severity based on their historical PEFR values. For our work in this paper, we segmented the data into "safe zone" PEFR values, which we take to be the upper 80% of the patient's historical distribution and "red zone" PEFR values, which are those in the lower 20%.

B. Hybrid Deep Learning Framework

Our proposed HDL framework consists of two main parts: (1) deep neural network as feature extractor, trained with traditional TL techniques and (2) conventional algorithms for classification. The framework pipelines these two parts: it trains a fully connected NN (source model) with population data of the 23 asthma patients excluding a target patient and then retrains the NN with the target patient's data. We refer to the resulting NN model as the *target model*. The output of the last hidden layer of the target model is considered as a set of hidden features extracted by the target model, and it is pipelined into a conventional classifier as input data. This step is in many ways a second transfer learning step, which enables us to hybridize a neural network that requires significant training data with a conventional classifier whose training requires much less data. Therefore, the final step of the transfer learning process that specializes the model to a single individual patient can be accomplished on the small data set of that single individual's data. In our experiments, we utilize five conventional classifiers: (1) Decision Tree (DT), (2) K-Nearest Neighbors (KNN), (3) Logistic Regression (LR), (4) Naive Bayes (NB), and (5) Support Vector Machine (SVM). Finally, the classifier produces a risk prediction decision (classification). Figure 2 shows an overview of the pipeline of NN and the conventional classification. The process executes as follows:

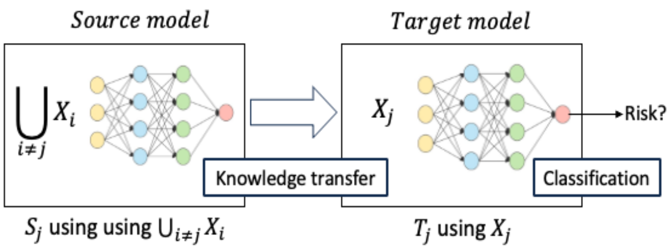
1) Train a fully connected deep NN using source data (population data: $D_{pop} = \bigcup x_i, i \neq j,\ i = 0, 1, 2, ..., n$) and save the source model S_j.
2) Retrain (fine-tune) the NN model using a target patient's data (individual data: $D_{ind} \leftarrow$ a patient j's dataset x_j) and store the model T_j.
3) Remove the output layer from T_j and connect the model to a conventional classifier. Feed the classifier with the outputs of the last hidden layer of the NN to train the classifier while freezing the NN.

We tested the HDL framework for asthma patients' health risk and the results of the experiments are presented in Section IV. Within the proposed framework, several variations can be explored as listed below:

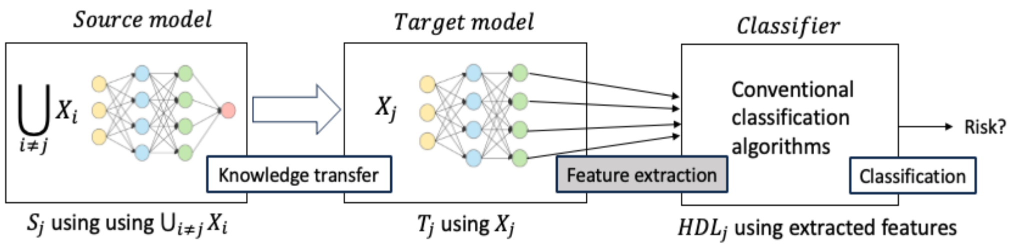
- Skip step (2) and freeze NN in step (3)
- Keep step (2) but do not freeze the NN in step (3)
- Skip step (2) and do not freeze the NN in step (3)

C. Feature Extractor NN

Because the feature extraction step is performed with a neural network trained with conventional transfer learning, this step can be extensively tuned for optimal final model performance using existing traditional TL techniques. The optimal architecture and hyperparameters for the neural network feature extractor will vary depending on the major characteristics of the available data. In this section, we describe the process by which we identified the optimal architecture, hyperparameters



(a) Traditional TL



(b) TL as feature extractor pipelined to conventional classifiers

Fig. 3: TL overview

TABLE I: Transfer Learning architectures

model	# frozen layers	architecture	unfrozen ratio
`TL1-0f`	0	[[32]]	100.0%
`TL2-1f`	1	[*[10, 20, 32], [10, 20, 32, 48, 64, 128]]	18.1 - 84.1%
`TL2-0f`	0	[[10, 20, 32], [10, 20, 32, 48, 64, 128]]	100.0%
`TL3-2f`	2	[*[10, 20, 32], *[6, 10, 20, 32], [4, 10, 20, 32]]	2.9 - 35.4%
`TL3-1f`	1	[*[10, 20, 32], [6, 10, 20, 32], [4, 10, 20, 32]]	19.9 - 83.2%
`TL3-0f`	0	[[10, 20, 32], [6, 10, 20, 32], [4, 10, 20, 32]]	100.0%
`TL4-3f`	3	[*[10, 32], *[32], *[10, 20, 32], [10, 20, 32]]	7.7 - 26.3 %
`TL4-2f`	2	[*[10, 32], *[32], [10, 20, 32], [10, 20, 32]]	18.5 - 51.9%
`TL4-1f`	1	[*[10, 32], [32], [10, 20, 32], [10, 20, 32]]	61.9 - 89.6%
`TL4-0f`	0	[[10, 32], [32], [10, 20, 32], [10, 20, 32]]	100.0%

$\star$ represents incoming parameters (weights) are frozen and unfrozen ratio = total number of parameters / unfrozen number of parameters

and TL training steps for the feature extractor NN. The main limitation of the training data in our case study is its relatively small size. Therefore, all of the networks studied in this paper are relatively simple feed-forward deep neural networks with an input layer, hidden layers, and an output layer returning a single value between 0 and 1 interpreted as the models confidence as to whether or not the patient's next-day PEFR value will fall below their critical PEFR value, i.e., 20% of their daily PEFR ($PEFR_C$). All model layers are connected with Rectified Linear Unit (ReLU) activation except for the output layer, which has sigmoid activation. As illustrated in Figure 3, the feature extraction NN is trained in two TL steps, which were explained more thoroughly in Section III-B. Step (1) trains the source model, and step (2) retrains the target model, which will be used as the final feature extractor.

In TL, the lower layers of the neural network, which capture general features, are often frozen, while the higher layers are fine-tuned to adapt to the new task-specific dataset. In this study, We tested a wide range of NN architectures along with various unfrozen ratios for the source model and the target model to find the best performing architecture and unfrozen ratios. The optimal architecture found, which we used for all of the HDL steps was model `TL3-0F` of Table I. Model `TL3-0F` was therefore used as the architecture for the feature extractor NN whose final hidden layer is used as input features to conventional classifiers in our experiments.

Table I presents the NN architectures used in our experiments, including the information of unfrozen ratio. For example, the model `TL3-2f` includes 3 hidden layers of sizes, 32, 20, and 20, respectively. Its architecture [*[32]-*[20]-[20]] indicates that its target model with the same layers that inherits the parameters of layers 1 and 2 from the trained source model but for which hidden layer 3 and the output layer are retrained on the target patient's data. For this particular architecture and frozen layers, the fraction of the source model's parameters made up by parameters that are unfrozen is 21.7%. We evaluate the proposed HDL framework comparing with this traditional TL model through extended experiments on real datasets.

TABLE II: Characteristics of datasets

Dataset	# data features	# samples	# minority (MI)	# majority (MA)	Imbalance ratio
23 asthma patients' datasets	27	88 - 210 (avg. 171)	16 - 57 (avg. 35)	72 - 172 (avg. 136)	2.32 - 5.73 (avg. 4.02)

TABLE III: TL training hyperparameters

Training Parameters	Hyperparameters
Optimizer	Adam (learning rate = 0.001)
# epochs	100 - 3,000
Batch size	16
Validation split rate	0.20 (source model), 0.33 (target model)

D. TL features pipelined to Conventional Classifier

In our study, we utilized this traditional TL to enhance the performance of classification models to overcome the scarcity of training data. The main idea is to use TL as feature extractor and feed a conventional classifier with new features from the TL model as a pipeline.

First, we remove the output layer from the fine-tuned target model T_j for a patient j and freeze all features (weights) of the model. We then connect the model to a conventional classifier so that the output of the last hidden layer of the target model are pipelined into the classifier as input data. Now we have the frozen target model as feature extractor and the conventional model as classifier. The classifier is then trained and validated using the patient's data X_j. An overview of the pipeline of TL and the conventional classifier is illustrated in Figure 3 (b).

E. Class Rebalancing

Although the focus of our study is on model improvement through transfer learning (TL) and deep learning, models are usually used with some form of data re-balancing to address class imbalance. Therefore in order to evaluate the performance of our proposed HDL method and make realistic comparisons to existing techniques, we conduct all of the performance comparisons on models combined with the Sample Density Distribution SMOTE (SDD-SMOTE) technique described in [7].

IV. Results

A. Datasets

Our datasets include 23 asthma patients' data consisting of values for 27 features collected through a case study [59]. All patients are non-smoking adults aged 45 to 83 years old, who participated in the ESCORT (environmental health smart study with connectivity and remote sensing technologies) study [59] between 28 December 2017 and 31 June 2018. The original study protocols related to our study were approved by the research ethics committee ofthe Soonchunhyang University (IRB No. 1040875-201608-BR-030); written informed consent was obtainedfrom all participants.

Each patient's dataset consists of physiological data such as peak expiratory flow rate (PEFR) as an indicator of asthma condition, behavioral attributes (house location, cooking style and income level), and environmental exposures to indoor and outdoor air quality variables, and differences of indoor and outdoor in several variables, which are known to be related to asthma exacerbation [60]. Patients' exposures to environmental variables were estimated using 24-hour time window at each PEFR measurement. Details of the data is shown in Table II.

Each data sample also comes along with along with a binary label as class 0 (minority) and class 1 (majority) where class 0 represents the patient's health risk zone and class 1 represents a non-risk zone. Class 0 (risk zone) is defined as a PEFR less than a patient's critical cutoff, PEFR_C, which is suggested by medical practitioners. In our study, we set PEFR_C to the 20% quantile PEFR value of a patient's dataset, so the data below PEFR_C are the minority class samples and the data above PEFR_C are the majority class samples.

B. Experimental Design

1) Performance Evaluation Metrics: Several standard evaluation metrics aim to fairly assess prediction model performance, but none perfectly measures performance in all applications. The metrics we used are: (1) weighted accuracy, (2) sensitivity, (3) specificity, (4) precision average, (5) F1-score average, and (6) Receiver Operating Characteristic Area Under the Curve (ROCAUC). While all these metrics are important, we focus on improving sensitivity scores because higher sensitivity means that a model is better at identifying high health risk.

2) K-Fold Validation and Hyperparameters: The effectiveness of the proposed HDL framework was tested on a combination of the feature extractor NN and five conventional classification algorithms. For each classifier, we trained the model on the training data augmented by SDD-SMOTE [7] and validated the performance of the classifier on non-augmented testing data.

Each dataset was split into 80% training/validation and 20% testing. Model hyperparameters were selected through extended training and validation processes using k-fold cross validation (CV) to avoid overfitting while increasing the performance of the models. The training data was augmented with synthetically generated data while the validation data and testing data retained the original imbalance ratio. Conventional classifiers used 3-fold CV, while TL classifiers used 5-fold CV for the source model and 3-fold CV for the target model, with

TABLE IV: Analysis of effect of unfrozen ratio in sensitivity

# of unfrozen layers	TL_{NN}	TL_{NN} + DT	$TLNN$ + KNN	TL_{NN} + LR	TL_{NN} + BN	TL_{NN} + SVM
4	0.4378	0.4014	0.4914	0.4402	0.4034	0.4350
3	0.3731	0.3868	0.4746	0.4491	0.3968	0.4233
2	0.4378	0.4257	0.4808	0.4867	0.4357	0.4636
1	0.3731	0.5152	0.5581	0.5484	0.5352	0.5269
0	**0.5378**	**0.6026**	**0.6515**	**0.6232**	**0.6276**	**0.6057**

Traditional TL model and HDL with architecture[[32], [32], [20], [20]] and 100 - 300 epochs.

TABLE V: Performance summary of classifiers: traditional TL over conventional classifiers

Classifier		Accuracy	Sensitivity	Specificity	Precision avg.	F_1 avg.	AUC ROC
Conventional Classifier	DT	0.5745	0.3742	0.7747	0.5704	0.5592	0.5745
	KNN	0.5967	0.5323	0.6611	0.5707	0.5522	0.5967
	LR	0.6180	0.5290	0.7089	0.5894	0.5805	0.6100
	NB	0.6141	0.4174	0.8109	0.6064	0.6018	0.6141
	SVM	0.5659	0.3266	0.8051	0.5614	0.5578	0.5659
TL_{NN}		**0.6853**	**0.5720**	**0.7982**	**0.6556**	**0.6543**	**0.6853**
Improvement over	DT	19.29%	**52.86%**	**3.03%**	14.94%	17.01%	19.29%
	KNN	14.85%	**7.46%**	**20.74%**	14.88%	18.49%	14.85%
	LR	10.89%	**8.13%**	**12.60%**	11.23%	12.71%	12.34%
	NB	11.59%	**37.04%**	**-1.57%**	8.11%	8.72%	11.59%
	SVM	21.10%	**75.14%**	**-0.86%**	16.78%	17.30%	21.10%

the Adam optimizer with binary cross entropy loss (learning rate = 0.001) and 100 - 3,000 epochs for both source and target models. Model training parameters are summarized in Table III. Our data analysis and experiments for classification models were developed in Python 3.8 and Keras framework.

To choose the unfrozen ratio and network architecture for a larger scale testing, we developed a testbed that used smaller size of epochs, 100 - 300. In our extensive experiments, we used 100 - 3,000 epochs for all modeling. We evaluated (1) the traditional TL model shown in Figure 3 (a) and (2) the feature extractor NN + conventional classifier shown in Figure 3 (b) using the architectures presented in Table I.

Across all tested models, most TL models produced the highest sensitivty score when their unfrozen ratio is 100%. This may be because training data of the source model is still too small to develop a general model and the prediction mostly depends on the target data. Table IV shows sensitivity scores of one of the tested model with a 3 hidden-layer architecture, [[32], [20], [20]] .

C. Experimental Results and Analysis

We evaluated the performance of the classifiers for 23 individual patients, which were developed in the proposed framework.

1) Comparison results of Traditional TL vs. Conventional Classifiers: First, we present the average performance analysis of the traditional TL model compared to five selected conventional classifiers. As shown in Table V, the traditional TL model consistently outperformed all conventional classifiers across key metrics, including weighted accuracy, sensitivity, precision, F_1 score and AUC ROC. This demonstrates the TL model's superior ability to generalize and make accurate predictions in comparison to traditional methods.

Although the average specificity score of the TL model was slightly lower than that of NB and SVM, it still outperformed DT, KNN and LR. The reductions in specificity compared to NB and SVM were minimal, with differences of just 1.57% and 0.8%, respectively. However, the TL model's improvements in the other metrics were much more pronounced. For example, sensitivity saw a significant increase, ranging from 7.46% to 75.14% across all classifiers. Similar trends were observed in accuracy, precision, F1 score, and AUC ROC, however changes in specificity were less consistent with traditional TL even showing slightly worse specificity compared with two conventional classifiers.

2) Comparison results of HDL over Traditional TL and Conventional Classifier: Second, we present a performance analysis of our proposed HDL models compared to both the traditional TL model and conventional classifiers. Across all evaluation metrics, the HDL models consistently outperformed the traditional TL model and this demonstrates the effectiveness of the hybrid framework.

Table VI shows the significant performance gains achieved by the HDL framework compared to the traditional TL model and conventional classifiers. Sensitivity improvements were particularly notable: +30.65% with DT, +42.45% with KNN, +34.39% with LR, +39.49% with NB, and +34.84% with SVM. The absolute sensitivity values, ranging from 0.7473 to 0.8148, suggest the proposed framework's strong potential for health-related predictions. These gains indicate that the HDL framework enhances the model's ability to accurately identify true positive cases. Similar improvements across other metrics, including specificity further emphasize the overall robustness of the HDL framework.

In addition to comparing average performance, we analyzed the distribution of evaluation metric values across individual patient models to gain a deeper understanding of performance variability. Figure 4 illustrates the distribution of evaluation metrics for 23 individual patient models, comparing the HDL framework with the traditional TL model as well as comparing

TABLE VI: Performance summary of classifiers: HDL vs. traditional TL vs. conventional classifiers

Classifier		Accuracy	Sensitivity	Specificity	Precision avg.	F_1 avg.	AUC ROC
Traditional TL	TL_{NN}	0.6853	0.5720	0.7982	0.6556	0.6543	0.6853
HDL	TL_{NN} + DT	**0.8019**	**0.7473**	**0.8564**	**0.7588**	**0.7668**	**0.8019**
	Improvement over TL_{NN}	17.01%	**30.65%**	**7.29%**	15.74%	17.19%	17.01%
	Improvement over DT	39.58%	99.71%	10.55%	33.03%	37.12%	39.58%
	TL_{NN} + KNN	**0.8446**	**0.8148**	**0.8744**	**0.7949**	**0.8060**	**0.8446**
	Improvement over TL_{NN}	23.25%	**42.45%**	**9.55%**	21.25%	23.19%	23.25%
	Improvement over KNN	41.55%	53.07%	32.26%	39.29%	45.96%	41.55%
	TL_{NN} + LR	**0.8290**	**0.7687**	**0.8893**	**0.7939**	**0.8012**	**0.8290**
	Improvement over TL_{NN}	20.97%	**34.39%**	**11.41%**	21.10%	22.45%	20.97%
	Improvement over LR	34.14%	45.31%	25.45%	34.70%	38.02%	35.90%
	TL_{NN} + NB	**0.8551**	**0.7979**	**0.9122**	**0.8270**	**0.8335**	**0.8551**
	Improvement over TL_{NN}	24.78%	**39.49%**	**14.28%**	26.14%	27.38%	24.78%
	Improvement over NB	39.24%	91.16%	12.49%	36.38%	38.50%	39.24%
	TL_{NN} + SVM	**0.8368**	**0.7713**	**0.9023**	**0.810**3	**0.8154**	**0.8368**
	Improvement over TL_{NN}	22.11%	**34.84%**	**13.04%**	23.60%	24.62%	22.11%
	Improvement over SVM	47.87%	136.16%	12.07%	44.34%	46.18%	47.87%

the traditional TL model with conventional classifiers. Figures on the left show the performance comparisons of the conventional classifiers and the traditional TL model and figures on the right show the comparisons of the traditional TL model and the HDL models.

The HDL framework exhibits considerably lower variability in performance metrics compared to the traditional TL model, demonstrating a more consistent model behavior across different patients. This reduction in variance is particularly significant for sensitivity, where the HDL framework significantly stabilizes performance. Similar patterns of reduced variability and improved consistency are observed across other key metrics.

While the TL model consistently outperformed the standalone conventional classifiers across all metrics, the improvements in variability across different patient models were minimal. This indicates that although the TL model offers better overall performance, it does not significantly reduce the performance variance between individual patients, indicating that variability remains a challenge in model consistency.

V. Discussion

In this paper, we proposed a hybrid deep learning (HDL) framework aimed at improving the prediction of rare events in medical applications with limited training data. By integrating transfer learning (TL) with conventional classification algorithms, we introduced a novel architectural strategy that effectively transfers knowledge from population-level data to individual patient models. Through extensive experiments on asthma patient data, we demonstrate the robustness and superior performance of the HDL framework compared to traditional TL and conventional classifiers. The framework demonstrates strong potential for practical use, with significant improvements in both performance and consistency across different classification methods. Future work will extend the application of this framework to other medical applications, such as disease severity diagnosis and hospital visit prediction.

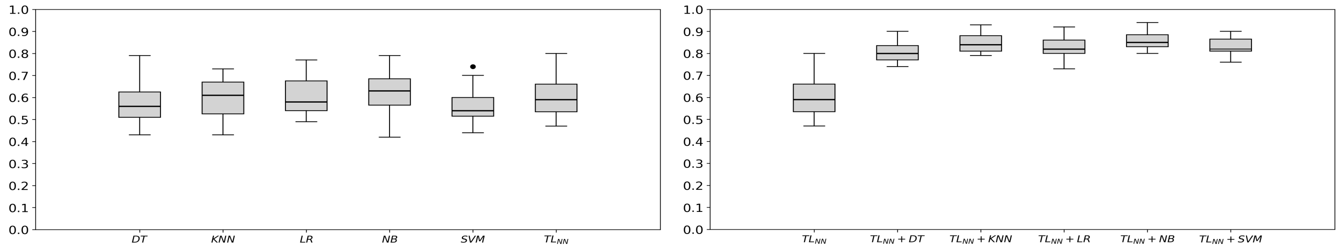
Our findings emphasizes the potential of machine learning techniques in personalized medical applications where data is sparse due to infrequent measurements. The population data used for the source model in our study —approximately 3,900 records from 23 patients— is still relatively small for deep learning models, and the massive gains achieved in other fields by significant increases in size and quality of training datasets suggest that as the population size increases, the HDL framework could offer even greater performance gains. This highlights its potential for further advancements in the future.

Because of the large number of different deep learning architectures available, determining the optimal deep architecture for any problem can be extremely time consuming. While that holds true for the neural network used as a feature extractor in our HDL framework, during our study to identify the optimal feature extractor architecture in this application we were able to observe consistent trends in final performance with respect to the exact portion of the source model to retrain. This suggests that manual fine-tuning strategies can help identify the optimal transfer learning architecture is no more onerous in the HDL framework than it already is in the traditional TL context. Furthermore, as more data becomes available, more systematic automated architecture selection strategies can be used.

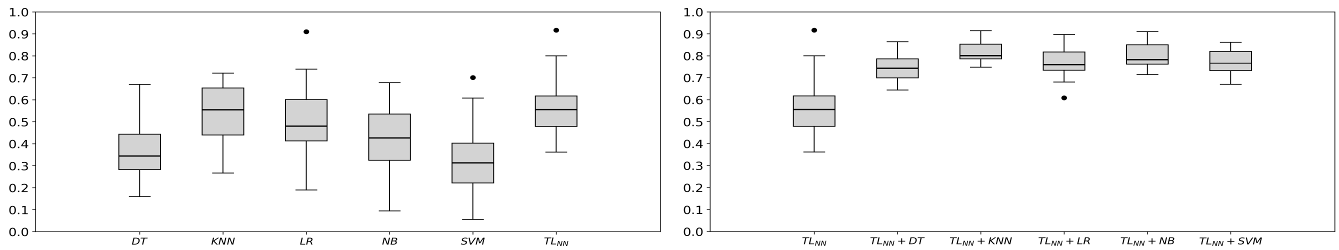
VI. Conclusion

Future work towards optimizing the specific architecture presented here could explore additional strategies to enhance the traditional transfer learning step within the HDL framework, including modifying the architecture of the source model before retraining, fine-tuning the source model with regularization techniques such as dropout, or using intermediate layers of the source model to initialize a smaller target model.

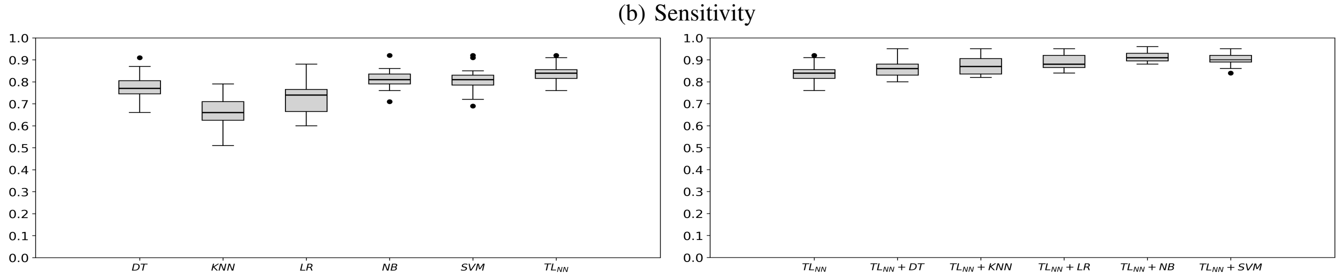
One direction that could be used to extend the HDL framework beyond what is presented in this paper is to utilize frameworks in which the training task for the feature-extraction portion of the model differs from the final target task of the full model. This is analogous to the training tasks used to train Word2vec and GloVe word embeddings in the field of Natural Language Processing, which are generally very different from the final tasks of models that use those embeddings. The first main challenge here, especially for medial applications, is the extreme heterogeneity of tabular



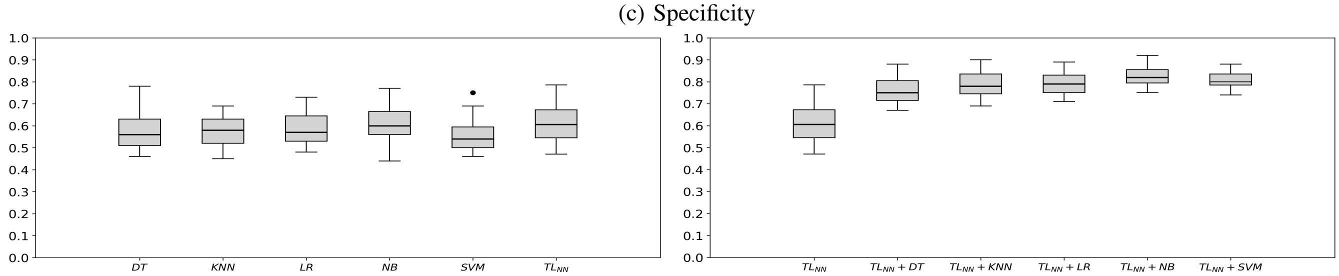
(a) Weighted accuracy



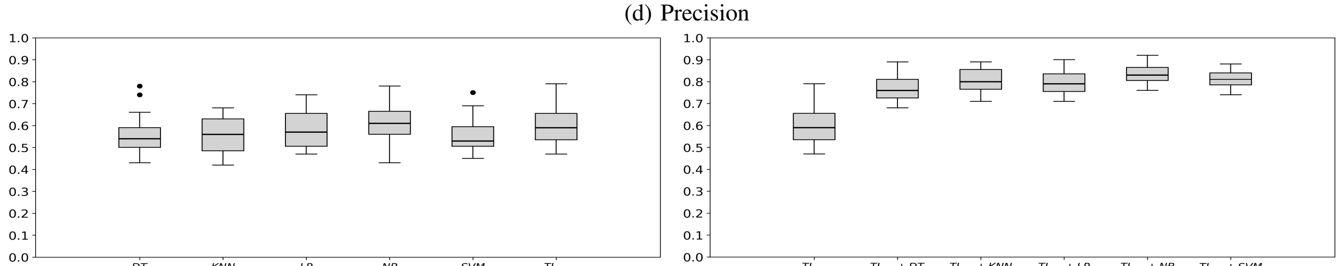
(b) Sensitivity



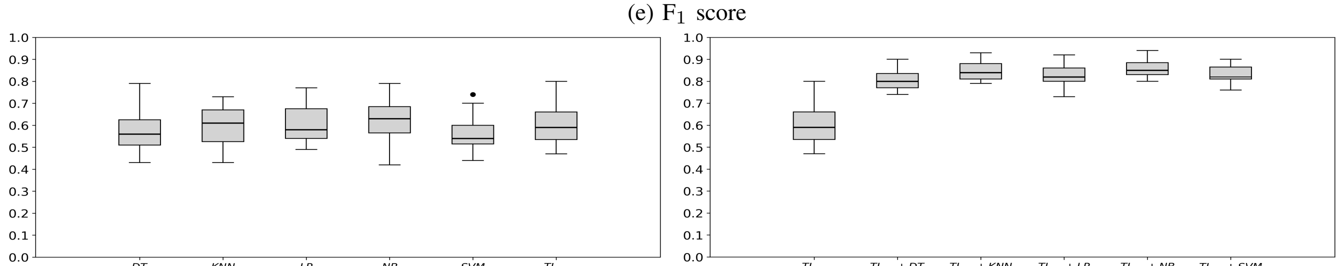
(c) Specificity



(d) Precision



(e) F_1 score



(f) ROC AUC

Fig. 4: Performance comparisons: Conventional Classifier vs. Traditional TL vs. HDL

data in many fields. Even datasets for different studies of the same disease rarely share many data attributes exactly. This contrasts with natural language processing and image processing in which the basic data entities of words and images are shared in the exact same format across extremely many specific tasks. If this challenge could be successfully overcome, it would enable training the feature extractor in an un-supervised or semi-supervised manner, which would open the door to a large number of more powerful and automated deep learning techniques.

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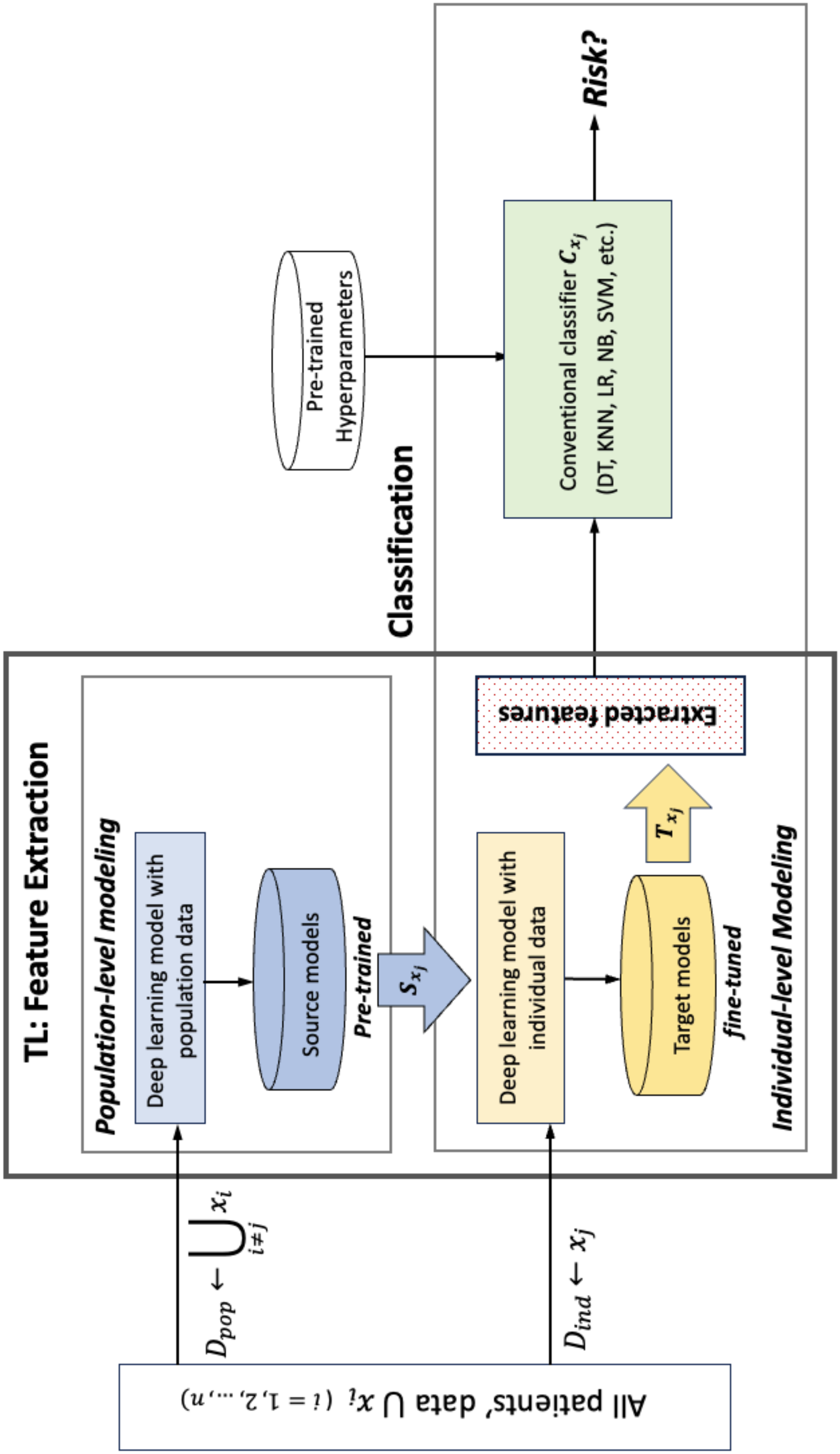

TL: Feature Extraction
Population-level modeling
Deep learning model with population data
Source models
Pre-trained
S_{x_j}
Individual-level Modeling
Deep learning model with individual data
Target models
fine-tuned
T_{x_j}
Extracted features
Classification
Pre-trained Hyperparameters
Conventional classifier C_{x_j}
(DT, KNN, LR, NB, SVM, etc.)
Risk?
$D_{pop} \leftarrow \bigcup_{i \neq j} x_i$
$D_{ind} \leftarrow x_j$
All patients' data $\bigcup x_i \quad (i = 1, 2, \ldots, n)$

A hybrid deep learning (HDL) framework that utilizes a neural network-based feature extractor trained with traditional transfer learning and then trains conventional classifiers with the extracted features. Through this hybrid deep learning method, new features are learned via knowledge transfer, and these fine-tuned features enhance the performance of conventional classifiers.

Workflow of the Hybrid Deep Learning Framework