Different Transfer Learning Approaches for Insect Pest Classification in Cotton

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Abstract

Boll weevil is an important pest that affects cotton crops worldwide, causing significant economic losses. The classification of the boll-weevil population is crucial for developing effective pest management strategies. However, the low availability of data and features makes classification a challenging task. This study aimed to investigate the use of Transfer Learning (TL) techniques to improve the classification of boll weevil populations. Three types of TL techniques, instance-based, feature-based, and parameter-based, were studied to improve the classification performance of the machine learning algorithms. This work used data from two domains, one with few instances and the other with few features, to test the proposed approaches. Also, climate variables (temperature, humidity, and rainfall) were incorporated as features to predict the level of the boll-weevil attack. The most relevant results of this work are that define 1) How to measure and quantify the similarity or relationship between tasks of different domains; 2) How to select, align, or adapt the relevant features, instances, or models from the source task/domain to the target task/domain; 3) How to reuse parameter settings from the source domain; and 4) How to evaluate and validate the performance and robustness of the TL model on the target task/domain. The proposed approach achieved significant improvements in classification over previous results in the metrics of accuracy and F-measure. For example, in the case with few instances reached an accuracy of 90.79%, while in the case with few features reached an accuracy of 96.28%. Thus, the results demonstrate the effectiveness of TL techniques in improving the classification of boll-weevil populations in cotton crops when few data and/or features are available.

Keywords: Transfer learning, Machine Learning, Artificial Intelligence, Insect pests, cotton management.

1. Introduction

Machine learning technologies have showcased the amazing capabilities of artificial intelligence in various technological applications. For example, with its multi-layered neural networks, deep learning excels in tasks such as image recognition and natural language processing (Huang et al., 2022; Thenmozhi & Srinivasulu Reddy, 2019). Reinforcement learning and deep reinforcement learning are also types of machine learning where an agent learns to make decisions in an environment based on reward feedback (Cuartas et al. 2023). They have demonstrated state-of-the-art performance in diverse domains, including game playing, robotics, and natural language processing technologies (Liu et al., 2022; Morales et al., 2019; Sánchez et al., 2020). Recently, quantum machine learning has emerged, combining quantum computing and machine learning algorithms (Zidan et al., 2021; Zidan et al., 2023), with the potential to solve complex problems beyond traditional techniques. These advancements continue to push the boundaries of AI. An area of machine learning of special interest in recent years is Transfer learning (TL), which utilizes pre-trained models to enhance learning on smaller datasets (Cody & Beling, 2023). TL techniques have shown remarkable success in improving the performance of machine learning algorithms by transferring knowledge from one domain to another (Xu et al., 2023).

On the other hand, the boll weevil (Anthonomus grandis) is an important pest that affects cotton crops worldwide, causing significant economic losses (Ben Guerrero et al., 2020; Grigolli et al., 2017). The classification of the boll-weevil population is crucial for developing effective pest management strategies (Toscano-Miranda, Toro, et al., 2022). However, the classification of boll-weevil populations is a challenging task due to the limited availability of data and features. Thus, traditional classification methods have been used to classify boll weevil populations, but they have limitations in terms of accuracy. For instance, a previous work developed models to classify the population of boll weevils (Toscano-Miranda, Hoyos, et al., 2022). The results achieved good precision (88%), however, there were limitations related to the number of instances and characteristics in some contexts studied. In this work, we attack these limitations with TL.

1.1 Related Works

TL techniques have been used to improve the classification of various pests in different contexts (Al Sahili & Awad, 2023; Coulibaly et al., 2022; Hadipour-Rokni et al., 2023; Huang et al., 2022; Li et al., 2021; Thenmozhi & Srinivasulu Reddy, 2019). For example, TL techniques have been used to improve the classification of pests in crops such as citrus fruit, and tomato (Hadipour-Rokni et al., 2023; Huang et al., 2022). Specifically, (Al Sahili & Awad, 2023) used TL to develop accurate models for agricultural classification tasks with few data. The study applied TL on ImageNet pre-trained models, where ImageNet was the generic dataset and AgriNet was the target dataset. The pre-trained models were then fine-tuned on the AgriNet dataset to improve their performance. The study found that VGG19 surpassed all other models with an accuracy of 94% and an F1 score of 92%. VGG16 was ranked second, followed by InceptionResNet-v2. The study evaluated the superiority of the proposed models using TL on two agricultural datasets. The AgriNet models achieved higher accuracies than the ImageNet models, and VGG19 was the best-performing model.

(Thenmozhi & Srinivasulu Reddy, 2019) used TL to retrain deep-learning models and improve the efficiency and accuracy of insect classification tasks. The study used a wide range of insect pests from different field crops such as rice, maize, soybean, sugarcane, and cotton crops. The pre-trained models such as AlexNet, ResNet, GoogLeNet, and VGG were used as fixed feature extractors. By fine-tuning the pre-trained models with TL, the proposed convolutional neural networks (CNN) model achieved higher accuracy in insect classification compared to the pre-trained models alone. The proposed model was evaluated on three different insect datasets, and it achieved high accuracy for each dataset (between 92.25% and 95.97%). The study also analyzed the effects of different hyperparameters on the performance of the proposed model.

Similarly, (Meena et al., 2023) used TL with pre-trained CNNs to be adapted by retraining them with smaller datasets, with a different distribution than the larger datasets used to train the network. In this study, multiple types of CNN architecture (Densenet 201, Mobilenet, VGG 16, Hyper-parameter Search, and Inception V3) were used on agricultural image data for plant leaf disease detection, pest detection, and weed detection. The fine-tuned Inception V3 model achieved 87.85% accuracy, while the Mobilenet and VGG 16 models achieved accuracies of 91.85% and 78.71%, respectively. The Densenet model performed well with 99.62% accuracy, and the Hyper-parameter Search had 71.07% accuracy. (Hadipour-Rokni et al., 2023) used TL with a deep learning model to leverage pre-existing knowledge from a previously trained model for a different task. The researchers used a pre-trained model on a large image dataset (ImageNet) to extract general features from the citrus fruit images and then fine-tuned the model using the dataset of citrus fruit images to classify the pests. The study found that TL was an effective technique for the early detection of pests in agricultural products using machine vision systems and deep learning. The AlexNet and GoogleNeT models had the highest accuracy (99.33% and 99.27%, respectively) in diagnosing citrus fruit disease, with the AlexNet model having the lowest calculation time. The study suggested that pre-trained models could be used in similar applications to save time and computational resources.

Additionally, (Coulibaly et al., 2022) used TL to improve the accuracy of the classification model in insect pests. TL used the Inceptionv3 model, which achieved an accuracy of 67.88% in the test set. By leveraging the pre-trained layers of Inceptionv3, the authors were able to reduce the number of network parameters by 41% without affecting the accuracy and loss classification. Also, TL made it possible to use visualization methods to understand what the model has learned, identify biases in the data that affect the training process, and debug the model to visualize these biases. Finally, TL contributed to improving the overall performance of the deep learning model in this study. (Huang et al., 2022) achieved that the knowledge learned from one problem was transferred to another problem in a different but related field. In this case, TL-based CNN models were used to identify tomato pests by transferring knowledge learned from other image recognition tasks. The authors improved the accuracy of tomato pest identification with CNN models (AlexNet, InceptionV3, VGG16, and ResNet50) and image augmentation technology. This approach improved learning efficiency and reduced training time. In summary, these studies used TL techniques with images to improve learning tasks in insect pest classification. However, to the best of our knowledge, the use of TL techniques to classify boll weevil populations has not been explored. Specifically, the use of TL techniques with structured data to classify boll weevil populations has not been analyzed. Therefore, there is a need to investigate the use of TL techniques to improve the classification of boll weevil populations.

In previous works, and to the best of our knowledge, the emphasis was usually on reusing previous models either to save training time or due to lack of data. There is no study that does an exhaustive analysis of how to work on cases where there is a lack of data and features in a problem at the same time. This work seeks to respond to this by proposing various TL schemes.

1.2 Contributions

This study aims to investigate the use of TL techniques to improve the classification of boll weevil populations by incorporating climate variables as features. Three types of TL techniques, instance-based, feature-based, and parameter-based, were studied to improve the classification performance of the XGBoost algorithm, which is the best machine learning algorithm for this type of task according to (Toscano-Miranda, Hoyos, et al., 2022). The study also aims to test the proposed approach using data from two domains, one with few instances and the other with few features. In summary, our study works with structured data about climate data, insect pest data, and three types of TL. The contributions of this study are the following:

- The definition of a procedure to measure/quantify the similarity or relatedness between two tasks or domains (called source and target). The experiments show how can affect the transferability and effectiveness of the knowledge transfer.
- The design of a method to select, align, or adapt the relevant features, instances, or models from the source task/domain to the target task/domain, which may require different strategies depending on the type and level of TL.
- The specification of a strategy to reuse parameter settings from the source domain and how to measure and determine their validity.
- The definition of a procedure to evaluate and validate the performance and robustness of the TL model on the target task or domain, with appropriate metrics and benchmarks.

The rest of the paper is organized as follows: Section 2 introduces the dataset of the boll weevil in cotton crops and the TL approaches existent in the literature. Section 3 presents the design of our approach of TL for the classification of boll-weevil populations. Section 4 shows the instantiation of our TL approach in different case studies in cotton crops. Section 5 presents the results of the case studies, and Section 6 concludes the paper by highlighting some of the future directions of this work.

2. Materials and method

2.1 Mathematical formulation of the TL problem

A domain D = D(X, P_x) consists of a feature space X and a probability distribution P_x for each feature $x \in X$. Given a domain of interest, a task T can be defined by a label space Y and a predictive function f: X -> Y.

In TL, we have two domains, a source domain D_s and a target domain D_t. On the other hand, we have that T_s corresponds to the task executed in D_s and T_t corresponds to the task performed in D_t. Thus, if we have D_s, then T_s is represented as (X_s, Y_s), and in D_t, T_t is represented as (X_t, Y_t). In our case, the objective is to find the parameters, instances or features W_t for the task T_t to determine Y_t. In this case, the idea is to minimize the equation:

$$argmin_{W_t}(C(X_t, Y_t))$$

where $C(X_t, Y_t)$ is the cost function defined on task T_t of domain D_t to determine Y_t (for example, the error); and W_t is the result of a TL process, which can be of parameters, instances or features.

2.2. TL approaches in the literature

According to (Pan & Yang, 2010), TL approaches can be divided into four categories: instance-based transfer, feature-based transfer, parameter-based transfer, and relational-based transfer. These categories provide a general framework for understanding the different approaches to transfer learning and are the basis for the development of new TL methods.

Instance-based transfer learning

According to (Pan & Yang, 2010), Instance-based TL is an approach that assumes that certain parts of the data in the source domain can be reused for learning in the target domain. Thus, the instance-based transfer involves transferring instances from the source domain to the target domain (see Fig 1). This approach involves measuring the similarity between a source and a target domain and selecting a similar source domain that has much more training data than the target domain. The approach can choose a pre-trained model that was learned from the source domain and fine-tunes it on the target domain using the re-weighted data (Pan & Yang, 2010; Yang et al., 2020). The rationale behind this approach lies in the premise that there are similarities between the source and target domains that can be exploited to improve performance in the target domain. By transferring specific instances from the source domain to the target domain, one seeks to leverage existing knowledge and adapt it to solve similar tasks in the new context. This technique becomes an effective strategy when the source domain has a large amount of training data and significant similarities to the target domain can be identified. However, this approach has its limitations and challenges. One of the potential problems is the assumption that instances from the source domain are applicable and useful in the target domain. If the similarities between the domains are not properly understood, or if there are subtle but significant differences between the data distributions of the two domains, instance-based transfer can lead to poor performance in the target domain. In addition, the quality of the transfer is highly dependent on the correct identification of the relevant instances and the similarity measure used to select them.

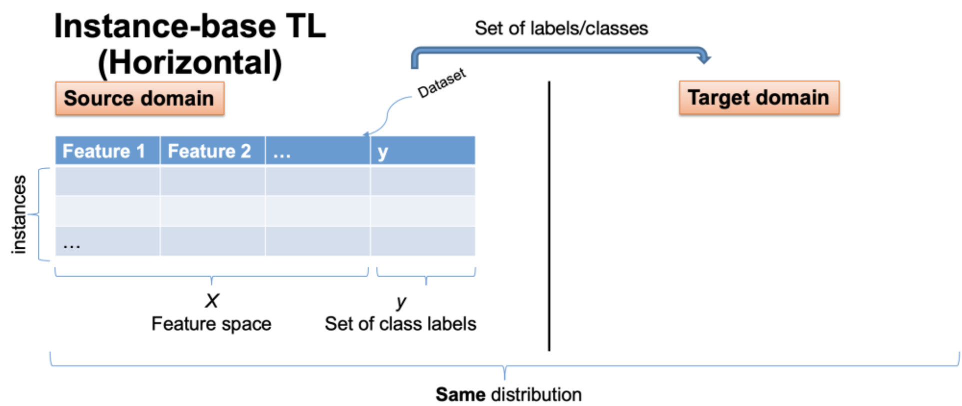

Fig. 1. Example of Instance-base TL

Feature-based transfer learning

Feature-based TL is an approach that involves transferring the feature representations learned from the source domain to the target domain (Aguilar et al., 2019; Pan, 2010; Pan & Yang, 2010). This approach assumes that the feature spaces between the source and target domains are similar or can be aligned. The learned features from the pre-trained model are then fed as input to a new model, which is trained on a different dataset or task. The advantage of feature-based TL is that it can be used when there is not enough data to fine-tune the entire pre-trained model, but still, the learned features can be useful in the new task (Oquab et al., 2014; Pan, 2010; Pan & Yang, 2010; Yosinski et al., 2014). Figure 2 shows the process of transferring features. The rationale behind the assumption that the feature spaces between source and target domains are similar or can be aligned is based on the idea that certain features relevant to a specific task can be generalized and reused in related tasks. Despite the logic behind the assumption, there are several limitations and factors that can affect the results of feature-based TL. For example, the introduction of learned features can lead to overfitting if the target dataset is small. On the other hand, while the learned features may be useful for generic tasks, certain tasks may require more specific knowledge that is not captured in the transferred features. In such cases, feature-based TL may not be sufficient to improve performance. Finally, in some cases, fine-tuning of the pre-trained model is necessary to better adapt it to the new task. Fine-tuning involves training some model settings on the new dataset to refine the learned features.

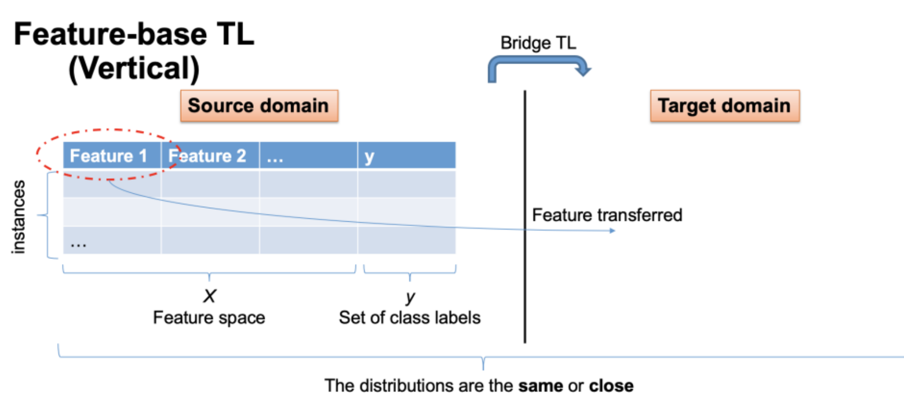

Fig. 2. Example of Feature-based TL.

Parameter-based transfer learning

Parameter-based TL is an approach that involves transferring the parameters, or prior distribution of hyperparameters, from the source domain to the target domain (see Figure 3). This approach assumes that the models for related tasks share some parameters or prior distribution of hyperparameters. This involves learning the source task first and then transferring the learned parameters to the target task. The pre-trained model is adapted to a new task by reusing some or all its pre-trained parameters, which are then fine-tuned on the new task using additional data. The advantage of parameter-based TL is that it can lead to higher performance on the new task, especially when the new task is like the pre-training task (Bashath et al., 2022; Chakraborty et al., 2022; Pan & Yang, 2010). The rationale behind this approach lies in the observation that certain features and patterns learned during the pre-training task may be applicable and relevant to the target task. By transferring the pre-trained parameters, the target model can benefit from this prior knowledge, which can speed up the training process and, in some cases, significantly improve performance on the new task. This is especially true when the target task is like the pre-training task. However, it is important to note that the success of parameter-based TL is highly dependent on the similarity between the source task and the target task. If the tasks are too different in terms of structure, nature of data or requirements, then direct parameter transfer may not be beneficial or even detrimental to performance on the target task. In addition, another critical factor that can affect the results of parameter-based TL is the quantity and quality of data available for the target task. If the target task data is sparse or of low quality, then pretrained parameter transfer may be more prone to overfit the model to the limited training data, leading to poor performance on unseen data. In such situations, it is important to consider strategies such as regularization and careful fine tuning to avoid overfitting.

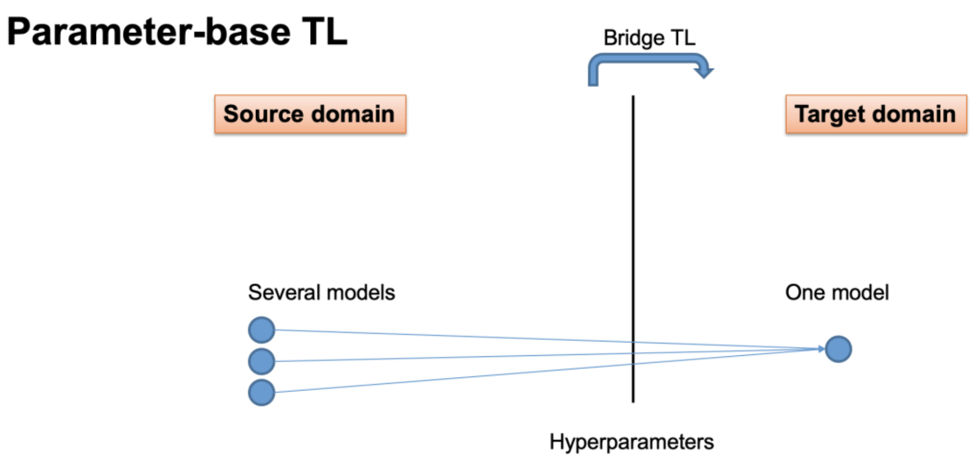

Fig. 3. Parameter-base TL.

Relational-based transfer learning

Relational-based TL is an approach that focuses on learning the relations between the source and target domains (Mihalkova & Mooney, 2009; Pan & Yang, 2010). Particularly, relational-based transfer involves transferring relational knowledge from the source domain to the target domain (see Fig. 4). This approach finds past knowledge in the source domain to be used in the current context by the target domain. This assumes that there is a relationship between the source and target domains that can be leveraged to improve the performance of the target task. Relational-based TL can be used in scenarios where the domains of the source and target tasks are not the same but interrelated (Day & Khoshgoftaar, 2017; Pan & Yang, 2010; Tan et al., 2017).

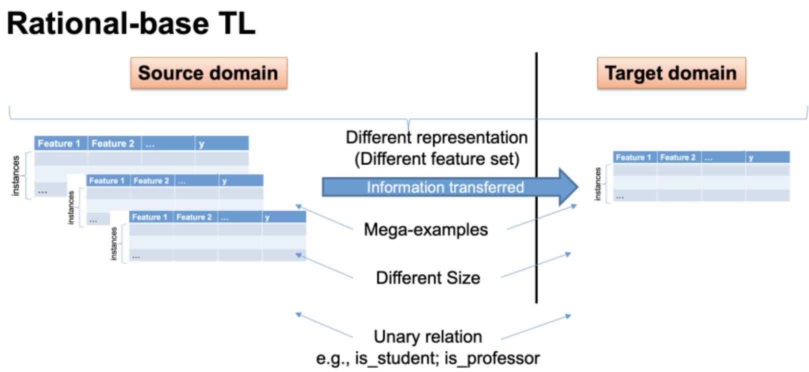

Fig. 4. Relational-base TL.

2.3 Study area and datasets

To validate our proposal, we utilized cotton crops as a case study, which are in various regions of Córdoba, Colombia. These regions include cities that make up the Sinú Valley, namely High, Middle, and Low Sinú, as mentioned in (Trebilcok, 2020), and are situated at approximately ~8°55'33.6"N, 75°48'16.5"W (see Fig. 5). We collected data for our study from the net of monitoring of the boll weevil established by the Colombian Agricultural Institute (ICA) and climate data recorded by the Colombian Institute of Hydrology, Meteorology and Environmental Studies (IDEAM). Specifically, we analyzed data from the cities of Montería, Cereté, Lorica, and Ciénaga de Oro, covering the period of 2018 to 2021. The reason for selecting these areas was due to their cultivation of cotton and the availability of pheromone trap records.

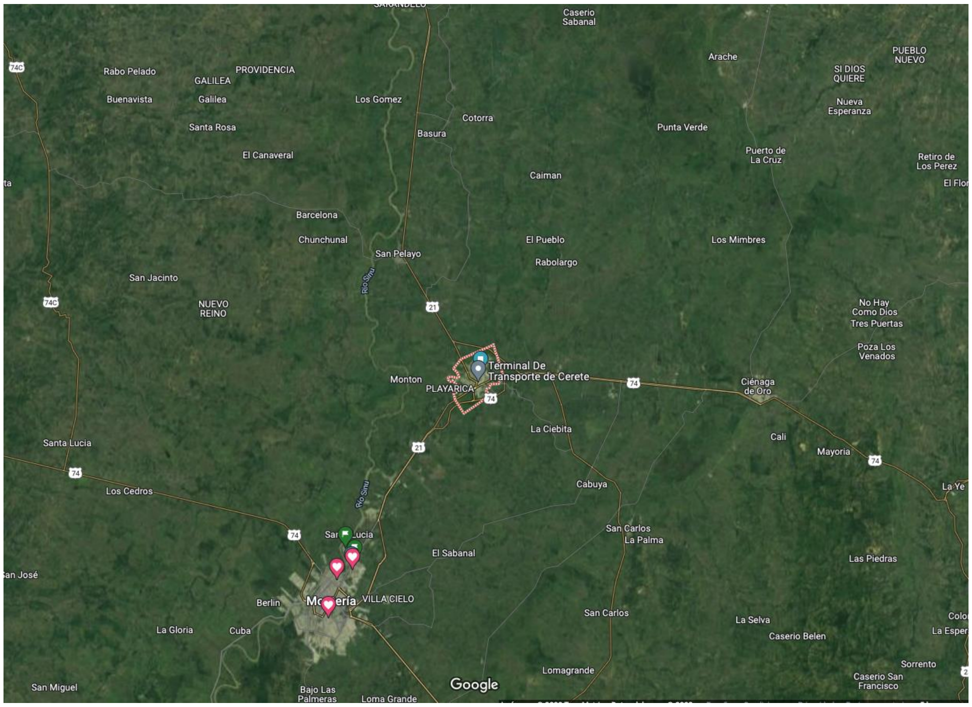

Fig. 5. Geographical regions of cotton crops in Córdoba

Datasets from regions of the Sinú Valley were used. These datasets included three climatic variables (rainfall, humidity, and temperature) and the number of red and black boll weevils captured in pheromone traps. *Rainfall* is the amount of rain that falls during the day, measured in millimeters. Rainfall can affect the survival and reproduction of boll weevils, as well as the growth and quality of cotton plants. *Humidity* is the hourly relative humidity (average of the day), measured in percentage. Humidity can also influence the development and activity of boll weevils, as well as the susceptibility and resistance of cotton plants to pests and diseases. *Temperature* is the average daily temperature, measured in degrees Celsius. Temperature can determine the life cycle and population dynamics of boll weevils, as well as the phenology and yield of cotton plants. *Red boll* weevils are the youngest stage of the pest, which has not yet reached maturity. This feature represents the number of captures of these boll weevils in a trap. Red boll weevils indicate the presence and intensity of infestation, as well as the potential damage to the cotton buds and flowers. *Black boll* weevils are the ones that can procreate, which have reached maturity and can mate and lay eggs. This feature represents the number of captures of these boll weevils in a trap. Black boll weevils indicate the reproductive capacity and the future generation of the pest, as well as the potential damage to the cotton bolls and seeds. Table 1 shows the distribution after processing and cleaning the dataset (Toscano-Miranda, Hoyos, et al., 2022). Lorica, Cereté included the climate variables and the red and black boll weevils. However, Ciénaga de Oro and Montería did not have enough samples for the red boll weevils and climatic variables. This particularity made it suitable to apply our proposal of TL.

Table 1. Dataset distribution.

City	Samples	Temperature	Humidity	Rainfall
Lorica	1800~	✓	✓	✓
Cereté	4000~	✓	✓	✓
Ciénaga de Oro	900~	✓	| ✓ Black	| ✓ Black
Montería	1000~	✓		| ✓ Black

We used five techniques, eXtreme Gradient Boosting (XGBoost), Random Forest, Decision Tree, Support Vector Machine, and Artificial Neural Network with multilayer perceptron, which were chosen because they have been techniques that have given very good results in previous works in various disciplines (Toscano-Miranda, Toro, et al., 2022). In that work, these techniques were subjected to a process of optimizing their parameters before comparing them, using the grid search hyperparameter optimization method (Aguilar et al., 2020). As a result of the comparison of these five techniques, XGBoost gave the best accuracy (88%). These analyses and results were presented in previous works (Toscano-Miranda, Hoyos, et al., 2022). Therefore, XGBoost is used in the present study.
In this work, several domains with few instances or few features are presented, which reach very poor quality metrics values compared to the domains with more instances and features. This is an opportunity to design and apply TL strategies, in order to improve the results of domains with few instances or features.

3. Design of our TL approaches

The TL was applied from the source domain (X^s) to the target domain (X^t) using a metric to determine the similarity between the domains. For the determination of this similarity metric, a statistical analysis with mean, standard deviation and variance was used. This study uses the instance-, feature-, and parameter-based TL techniques. In the next subsections, we will describe each technique in our work.

Instance-based transfer learning

This technique uses a horizontal treatment of the data set (that is, samples/instances). From now on, we will call them instances. The source domain transfers data because the datasets of the target domain are few. Fig. 6 shows the use of the instance-based TL approach. We use the similarity of the instances with all the features (F1, F2, F3) between the source domain and target domain to compare the different sources. The source domain that has major similarity with the target domain, and also, good accuracy, is selected. Thus, this process generates new instances in the target domain according to the similarity of the instances.

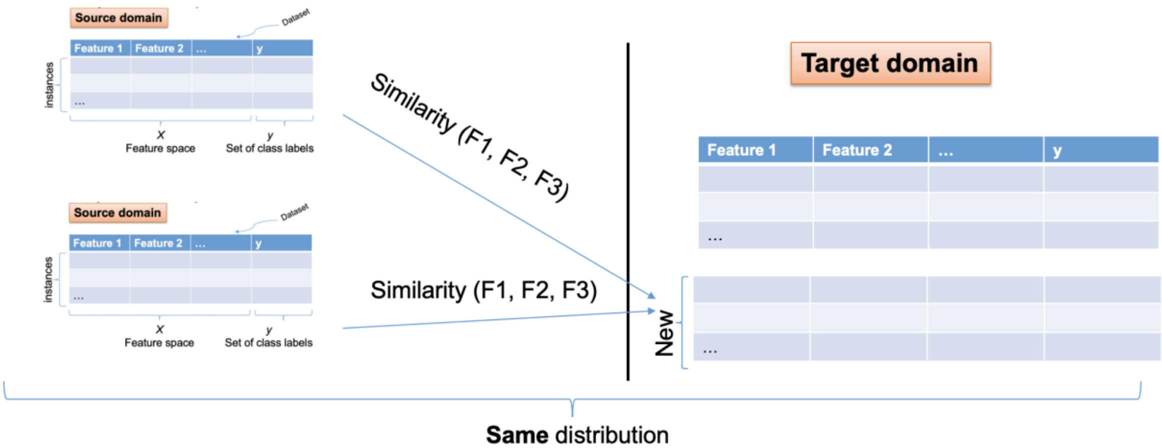

Fig 6. Instance-based TL in our case study.

Algorithm 1 shows the steps to reach the instance-based TL. A similarity threshold is defined to establish the instances to select. Instances with a similarity greater than 75% were selected. Thus, during step 4 of algorithm 1, the instances of the source domain that are like the target domain are determined, and then, added to the target domain dataset as new instances. Then, in step 5 of algorithm 1, the model for the target domain is trained with both old instances and new instances. Finally, in step 6, the set of tests is used in the model of the target domain to evaluate its quality.

Algorithm 1: instance-based TL algorithm

Input:
X^s: Source domain of boll weevil
X^t: Target domain of boll weevil

Output: TL in the target domain

1. Train several X^s_i
2. Test X^s_i
3. Analysis of statistical similarity of all instances of the best X^s_i‘s vs X^t, using the features F1, F2, F3
4. The best instances similar to the selected X^s_i pass as new instances to the X^t
5. Train with the entire X^t with the new instances
6. Test X^t

Feature-based transfer learning

This technique uses a vertical treatment of the dataset. We used as the source domain the datasets of the cities with the best accuracy and similarity to the target domain. Suppose we have three features (e.g., F1, F2 and F3). The selected source domain transfers features to the target domain because the target domain datasets do not have all the features (missing features, e.g., F2 and F3). We applied statistical similarity of the common features (i.e., F1) between possible source domains (with good accuracy) and the target domain to select one of them. Like the previous technique, samples were selected whose features (columns) obtained a similarity greater than 75%. Then, F2 and F3 from the selected source domain are transferred to the target domain (see Fig. 7). Note that the similarity analysis was made based on the statistical metrics of F1.

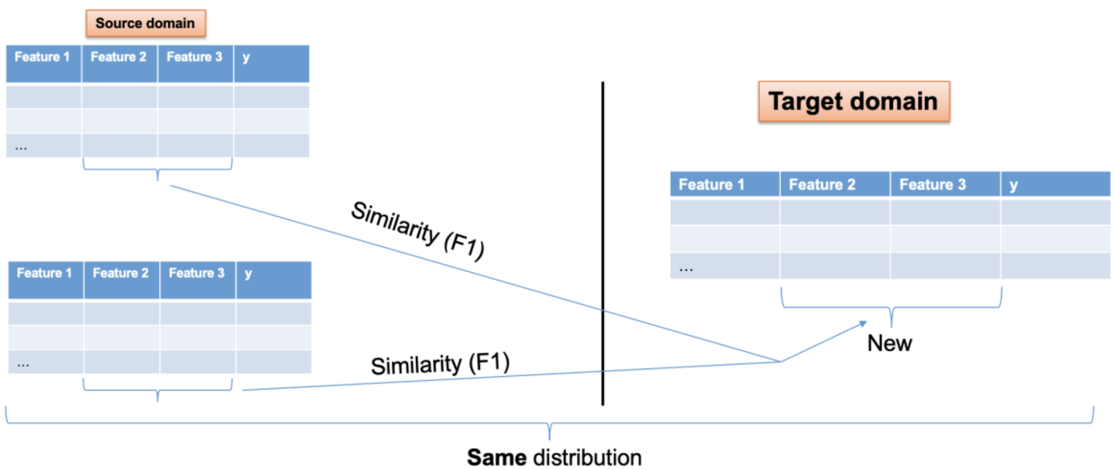

Fig. 7. Feature-based TL in our case study.

Algorithm 2 shows the steps to reach the TL. A similarity threshold was defined to establish the instances to select. In this case, samples were selected whose features (columns) obtained a similarity greater than 75%. In step 3.2 of algorithm 2, the source dataset whose F1 is most similar to the F1 of the target dataset is selected. Then in step 4, the most similar instances according to feature F1 of the selected source dataset are selected to take their other features. In step 5, the new features (F2, F3) are added to the target domain dataset. Finally, the model of the target domain is trained and tested with both the old and new features (see steps 6 and 7).

Algorithm 2: feature-based TL algorithm

Input:
X^s: Source domain of boll weevil
X^t: Target domain of boll weevil

Output: TL in the target domain

1. Train several X^s_i
2. Test X^s_i
3. Select the best X^s_i's

3.1 Analysis of similarity of F1 (temperature) between each selected X^s_i and X^t

3.2 Select the X^s_i more similar to X^t

4. Select the instances more similar from the selected X^s_i (according to F1)
5. The instances more similar pass to the target domain with their new features (F2, F3) to the X^t
6. Train with the entire X^t with the new features
7. Test X^t

Parameter-based transfer learning

With the parameter-based TL technique, we improved the target domain (X^t) using the parameters of the best model applied to the source domain (X^s). For this purpose, firstly, we selected the best model trained on the source domain. Second, we transferred the parameters of this model to the model of the target domain to improve it. Source domains (X^s) are those machine learning models with the highest precision and whose data sets it trained on have a most statistically similar to the target domain (X^t). The most similar and best model is the one used to transfer all its parameters (see Fig. 8).

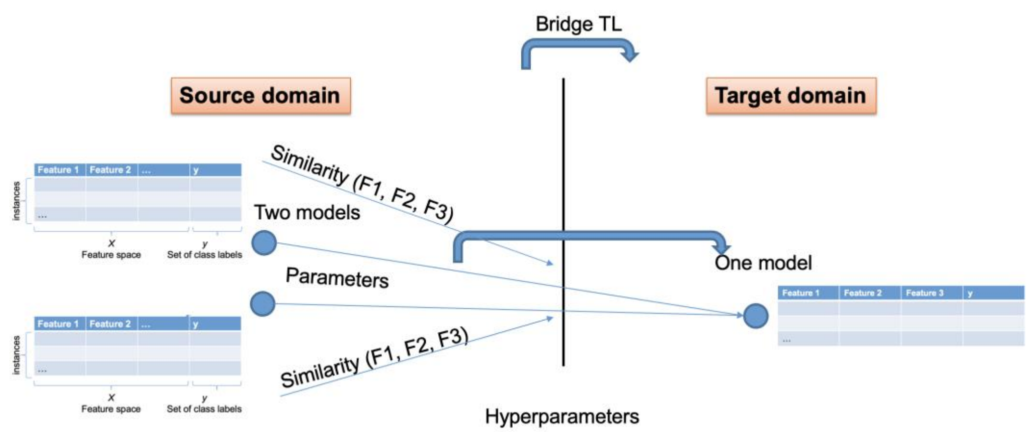

Fig. 8. Parameter-based TL in our case study.

Algorithm 3 shows the steps to reach the TL. The best source domain is selected for transferring its parameters to the target domain (see steps 3.1 and 3.2). In step 4, the model of the target domain is trained with the new parameters. Finally, in step 5, testing is performed with the target domain model.

Algorithm 3: parameter-based TL algorithm

Input:

X_1^s: Source domain of boll weevil

X_2^s: Source domain of boll weevil

X^t: Target domain of boll weevil

Output: TL in the target domain

1. Train several X^s_i's
2. Test X^s_i's
3. If the accuracy of X^t is not good
   3.1 Select the best X^s_i
   3.2 Transfer the parameters of the selected X^s to X^t
4. Train X^t with the transferred parameters
5. Test X^t

4. Instantiation of our TL approaches in our Case study

TL techniques were applied using the XGBoost algorithm. XGBoost is the technique with the best results in previous works (Guo et al., 2020; Liu et al., 2020; Tawalbeh et al., 2020; Toscano-Miranda, Hoyos, et al., 2022). The experiments included the datasets with information about climate data (temperature, rainfall, and humidity) and the level attack of the red boll weevil. The black boll weevil obtained low accuracy in all the cases (lower than 70%) in a previous work (Toscano-Miranda, Hoyos, et al., 2022), and therefore, it was not used in this study.

Table 2 shows the distribution of the dataset in each city and the TL technique that was used in each case study. In previous work, Lorica city had the best results of accuracy in the classification model (see Table 2 and (Toscano-Miranda, Hoyos, et al., 2022)). The city of Cereté had more samples but less accuracy than the city of Lorica. Therefore, we used parameter-based TL from Lorica to Cereté to improve its accuracy. Ciénaga de Oro city has less samples than Lorica city, therefore, we used instance-based TL from Lorica to Ciénaga de Oro to improve its accuracy using the similarities between these domains. Monteria city did not have all the climatic data. Montería only had the temperature. Therefore, we used with Montería city a feature-based TL approach to improve the accuracy using the statistical similarity between the common features.

Table 2. Dataset distribution vs TL technique.

City	Remarks	Samples	TL	Previous Accuracy
Lorica	The best accuracy. Used as a source domain	1800~	NA	88%
Cereté	With more instances. Used as source and target domains	4000~	C	76,68%
Ciénaga de Oro	Used as a target domain	900~	A, C	NA
Montería	Used as a target domain	1000~	B	NA

Abbreviations: A = Instance-based TL, B = Feature-based TL, C = Parameter-based TL, NA = Not apply

Eq. (1) and Eq. (2) were used to determine the similarity between source and target domains. The similarity of each feature is given by:

$$S(i) = \left[1 - \frac{\left|X^{i}_{source}\right| - X^{i}_{target}}{max\left(X_{target}\right)}\right] \tag{1}$$

where *i* indicates the current feature, S is the percentage of similarity, X_{source} is the source domain, X_{target} is the target domain.

The similarity of all features per instance is given by,

$$S(h) = \frac{1}{n}\sum_{i=1}^{n} S(i) \tag{2}$$

where *h* is the current instance and *n* is the number of features.

Instance-based transfer learning

The purpose of this technique was to improve the target domain (Ciénaga de Oro) using as the source domain Cereté and Lorica. In a previous work (Toscano-Miranda, Hoyos et al., 2022), the Ciénaga de Oro domain failed because it did not have enough instances in each class. The dataset of the target domain had 985 instances. The quantity of red boll weevil captured in pheromone traps was recorded and classified as Low, Medium, and High. The Low class means the number of red boll weevils between 0 to 4. The Medium class means the number of red boll weevils between 5 to 20. High class means the number of red boll weevils is greater than 20. For the Low class, there were 946 instances with information about of the number of boll weevils, 36 for Medium, and 3 for High (see Table 3).

Table 3. Target domain: Distribution of the quantity of instances per Low, Medium, and High class.

Class of boll weevil	Instances
Low (0 to 4)	946
Medium (5 to 20)	36
High (> 20)	3
Total	985

In this case, the oversampling technique failed in the target domain due to there were few instances in the High class.

Feature-based transfer learning

In a previous work ((Toscano-Miranda, Hoyos, et al., 2022), the results of the Montería domain only included the feature of temperature. For this reason, it was selected as the target domain in this study. Thus, the Montería dataset is the target domain because it has one feature of climate. In our case study, we used as the source domain the datasets of the cities with the best accuracy (i.e., Lorica and Cereté). The source domains have three features (temperature, humidity, and rainfall).

We applied statistical similarity of the common features (in this case, the temperature) between the possible source domains and the target domain. Feature 2 (humidity) and feature 3 (rainfall) from the selected source domain, are then transferred to the target domain according to the similarity of feature 1 (temperature) between the selected source domain and the target domain. The similarity analysis was made based on Eq. (1).

The source domain included climate data (temperature, rainfall, and humidity) and the level attack of the red boll weevil (i.e., categorized as Low, Medium, or High class). The two domains were compared focusing on the common feature (temperature). If the instance of the target domain was in the same class (level attack Low, Medium, or High) of the source domain, then Eq. (1) was applied to determine the percentage of similarity between the feature of the temperature of the target domain and source domain. If the feature was in the threshold of similarity, then the other two features (humidity and rainfall) were transferred as new features to the target domain (for the same instance).

For the target domain, 1052 instances with only one feature were analyzed. In the source domains, 1775 and 4083 instances with three features were analyzed (see Table 4). In summary, only the temperature features that reach the similarity threshold are considered to pass their features to the target domain as new features.

Table 4. Target domain and source domains with their instances and features.

			Features		
City	Domain	Instances	*Temperature*	*Humidity*	*Rainfall*
Montería	Target	1052	✓		
Lorica	Source	1775	✓	✓	✓
Cereté	Source	4083	✓	✓	✓

Parameter-based transfer learning

In our case study, first, we selected the dataset of the city of Cereté as the target domain. Second, we use a parameter-based TL to improve its model results. We used the machine learning models developed by the dataset from the city of Lorica as source domains to improve the machine learning models from the city of Cereté. Thus, the parameters of the best models in the selected source domain are transferred to the model in the target domain. The Cereté dataset was used as the target domain because the precision was lower than that of Lorica. Thus, this technique used the configuration of the parameters from the source domain to the destination domain. In this way, this experiment aims to reduce the time to configure hyperparameters in the target domain.

5. Results

In this section, the proposed approaches to improve the prediction using TL paradigm are presented. The results of ((Toscano-Miranda, Hoyos, et al., 2022) were improved with our three techniques of TL. Based on the confusion matrix, three metrics (Accuracy, Recall, and F1 score) were used to evaluate the performances of our models. These metrics are given by (Pacheco et al., 2014),

$$Accuracy = \frac{Number\ of\ boll\ weevil\ correctly\ predicted}{Total\ number\ of\ input\ boll\ weevil\ samples}$$

$$Recall = \frac{Number\ of\ boll\ weevil\ correctly\ predicted}{Total\ number\ of\ true\ cases}$$

$$F1\ score = 2 * \frac{Recall * Accuracy}{Recall + Accuracy}$$

Additionally, to test the results of our parameter-based transfer learning approach, we defined the following hypotheses (Vizcarrondo et al., 2012; Sánchez et al., 2016):

$$H_0: \bar{\gamma}_{TL} = \gamma_{no-TL}$$

$$H_1: \bar{\gamma}_{TL} > \gamma_{no-TL}$$

where $\bar{\gamma}_{TL}$ is the accuracy mean of 1000 runs on the testing set using the parameters transferred from Lorica city and γ_{no-TL} corresponds to the accuracy of the model without the application of transfer learning. To test the hypotheses, the Student's t test with superior tail alternative and 95% confidence was used. Finally, for each of the case studies, the XGBoost parameters were optimized using the grid search hyperparameter optimization method (Aguilar et al., 2020).

Instance-based transfer learning

In this case study, we used as source domain the datasets of the cities with the best accuracy (i.e., Lorica and Cereté cities). The target domain was Ciénaga de Oro. After applying Eq. (1) and Eq. (2), the experiments were conducted with 75%, 90%, and 95% of similarity. Also, three experiments were conducted: The first experiment included the source domain of Cereté and the data of the red boll weevil. The second experiment included the source domain of Lorica and the data of the red boll weevil. The third experiment included the source domain using the combination of instances of Cereté and Lorica with the data of the red boll weevil.

The two domains (source and target) were compared using the algorithm (1): if the instance of the target domain was in the same class (Low, Medium, or High-level attack) as the source domain, then the Eq. (2) was applied to determine the percentage of similarity. If the instance was in the threshold of similarity, then it was transferred as a new instance to the target domain. Finally, new instances were added, with a minimum of 170.56% (see Table 5) and a maximum of 691.68% (see Table 6) of increase. Table 5 shows the increase of new instances in the target domain using the best results from the best source domain (Lorica) and different similarity thresholds (A, B, C).

Table 5. Increase of new instances in the target domain.

Class	S-L	T-C-O	T-C-TL		
	Instances	*Instances*	*A*	*B*	*C*
0	1668	946	2614	2591	2544
1	95	36	129	127	113
2	12	3	11	8	8
Total	1775	985	2754	2726	2665
Increase of new instances:			1769	1741	1680
Percentage increase:			179.59%	176.75%	**170.56%**

Similarity between source and target domains: A: 75%, B: 90%, C: 95%.
Abbreviations: S-L= Source Lorica, T-C-O: Target - Ciénaga de Oro - Original, T-C-TL: Target - Ciénaga de Oro - Processed with TL.

Table 6 shows that the combination of the two source domains (Lorica and Cereté) added more instances than just Lorica (shown in Table 5).

Table 6. Increase of new instances in the target domain using as source domains the combination of Lorica and Cereté

Class	S-LC	T-C-O	T-C-TL		
	Instances	*Instances*	*A*	*B*	*C*
0	5510	946	7402	7379	7332
1	268	36	338	334	276
2	80	3	58	23	11
Total	5858	985	7798	7736	7619
Increase of new instances:			6813	6751	6634
Percentage increase:			**691,68%**	685,38%	673,50%

Similarity between source and target domains: A: 75%, B: 90%, C: 95%.
Abbreviations: S-LC= Source Lorica+Cereté, T-C-O: Target - Ciénaga de Oro - Original, T-C-TL: Target - Ciénaga de Oro - Processed with TL.

The target domain was then balanced with SMOTE and normalized with StandardScaler. Table 7 shows the results of the experiments with the different combinations of the source domains and the similarity threshold. The results showed that the model was improved and gave an accuracy of 90.79%.

Table 7. Results for the set of testing using the target domain to Ciénaga de Oro and three source domains.

Source domains	A		B		C	
	Accuracy	*F1-Score*	*Accuracy*	*F1-Score*	*Accuracy*	*F1-Score*
Cereté	0.8329	0.8329	0.8821	0.8821	FoO	
Lorica	0.9018	0.9018	0.9074	0.9074	**0.9079**	**0.9079**
Lorica + Cereté	0.8982	0.8982	0.8862	0.8862	0.8875	0.8875

Similarity between source and target domains: A: 75%, B: 90%, C: 95%

In general terms, the results showed that the accuracy increased with the similarity. It means that using 95% of similarity as the threshold gave the best results. Also, of the source domains used, Lorica showed the best accuracy. It is worth mentioning that experiments with 98% of similarity failed in oversample. Also, the results show that the instance-based TL gave better results in Ciénaga de Oro city (90.79%), compared with the best result of Lorica city (88%) found in (Toscano-Miranda, Hoyos et al., 2022). In general, with least similarity threshold, the experiments gave less precision, although more instances were added (see Tables 5 and 6). On the other hand, with the source domain of Lorica is obtained the best results than with other combinations (e.g., Cereté, or Lorica + Cereté). Finally, instance-based TL helped a target domain that was having trouble finding predictions because it didn't have enough instances can now achieve higher accuracy. The results showed that instance-based TL can achieve high accuracy rates by selecting the most similar instances from the source domain to the target domain, based on a similarity measure. This reduces the negative transfer and increases the relevance of the transferred data.

Feature-based transfer learning

In this case study, we use as source domains the datasets of the cities with the best precision (i.e., the cities of Lorica and Cereté) and as the target domain to Montería. The datasets included information related to the red boll weevil and climate data. Four experiments were conducted. In each experiment, two new features were added to the target domain using Eq. (1), and then, further actions were applied as follows: The first experiment used class balanced with SMOTE. The second experiment included new instances belonging to the High class of boll-weevil attack level. These instances were manually selected. Then, the entire dataset was balanced with SMOTE. In the third experiment, SMOTE was not used. The fourth experiment applied an automatic hybrid technique (feature-based plus instance-based). After adding the two features using feature-based TL, new instances were automatically added using instance-based TL by Eq. (2). Then, the dataset was balanced with SMOTE. Table 8 shows a summary of these experiments.

Table 8. Description of the four experiments with feature-based TL.

Experiment	Description
First (SMOTE)	Two features were added, and the dataset was balanced with SMOTE.
Second (Hybrid: Manual + SMOTE)	Two features were added. Additionally, a set of instances of the High class of boll-weevil attack level were selected of the source domain and added to the target domain. This set of instances had three features. Then, the dataset was balanced with SMOTE.
Third (Pure)	Two features were added.
Fourth (Automatic hybrid)	Two features were added. Then, new instances were automatically added using the instance-based TL approach Finally, the dataset was balanced with SMOTE.

In summary, of the four experiments to test the feature-based TL approach, two experiments had instances added (manually or using the instance-based TL approach) and the other two did not. The experiments were conducted with 75%, 90%, and 95% of similarity.
Table 9 shows the results of the four experiments with the three similarity thresholds. The first experiment had better quality by including the source domain of the city of Lorica and the oversampling technique with SMOTE. This was because similarity was better between the temperature characteristic of the source and target domains, compared to the other three experiments. The second experiment gave a lower precision than the first, although the difference was small. Manually selecting certain instances helped but was not the best strategy. The third experiment with the pure technique could not oversample because there were not enough instances in the high class. Finally, the results showed that the predictive model improved with the feature-based TL technique and gave an accuracy of up to 96.28%, surpassing the results of the city of Lorica (88%) found in (Toscano-Miranda, Hoyos et al., 2022). The feature-based TL technique demonstrates that it is possible to transfer learning from one domain to another. The results showed that feature-based TL can achieve high accuracy rates by using cross-domain feature similarity analysis, allowing those features to be reused in the target domain to enrich its information and build more robust models.

Table 9. Results for the set of testing using the target domain to Montería and four experiments source domains.

Experiment	A		B		C	
	Accuracy	*F1-Score*	*Accuracy*	*F1-Score*	*Accuracy*	*F1-Score*
First (SMOTE)	0.9442	0.9442	0.93	0.93	**0.9628**	**0.9628**
Second (Hybrid: Manual + SMOTE)	0.9256	0.9256	0.9344	0.9344	0.9584	0.9584
Third (Pure)	FoO	FoO	FoO	FoO	FoO	FoO
Fourth (Automatic hybrid)	0.887	0.887	0.8928	0.8928	0.8836	0.8836

Similarity between source and target domains: A: 75%, B: 90%, C: 95%. Abbreviation: FoO = Fail on oversample.

Parameter-based transfer learning

The purpose of the experiment was to assess whether the best model for one city could result in better classification results for Cereté. As a hyperparameter optimization process was carried out in XGBoost, we transferred the values of the parameters with which the best performance of the model was obtained, which significantly affected the results. Table 10 shows the hyperparameters transferred from the source domain to the target domain, based on the previous work (Toscano-Miranda et al., 2023), where a significant number of hyperparameters were tested and it was found that those defined in Table 10 are the ones that are really relevant to obtain the best possible model. To mention one example, the parameter called *min_weight_fraction_leaf*, which defines the minimum weighted fraction of the total sum of weights, was not carried over because it does not affect the model performance. Other parameters such as *min_impurity_decrease, random_state, verbose*, among others, also do not contribute to the superior performance of the model, therefore, they were not transferred either.

Table 10. Brief description of parameters transferred from the source domain to the target domain.

Parameter	**Brief description**	**Value**
subsample	The portion of samples allocated for fitting the individual base learners.	0.8
n_estimators	The quantity of boosting rounds to execute.	1000
min_child_weight	denotes the smallest total weight a node must have to split into a child.	1
max_depth	Defines the depth of the tree based on the quantity of splits performed.	4
learning_rate	Reduces the tree weights in each round of boosting	0.4

Table 11 shows the mean and standard deviation of the metrics that evaluate the performance of the models. Additionally, it shows the results of the statistical test to check if the use of TL allows the improvement of the performance of the model without TL. Based on the results, the use of the parameter-based TL approach significantly improves the performance (accuracy and F1-score) of the model without TL (p-value = < 0.001).

Table 11. Descriptive statistics and Student's t-test (p-value) results to determine performance improvement using TL.

Metric	$\bar{\gamma}_{TL}$	σ_{TL}	γ_{no-TL}	p-value
Accuracy	0.792	0.006	0.670	< 0.001
F1-Score	0.771	0.006	0.710	< 0.001

In summary, the results showed an increase in accuracy levels from 67% to 79.2%. In other words, the parameters that worked best for Lorica (88%) also performed better in Cereté.

6. Comparison with previous works

This study aimed to investigate the use of TL techniques to improve the classification of boll weevil populations. Three types of TL techniques, instance-based, feature-based, and parameter-based, were studied to improve the classification performance of the machine learning algorithms. We introduce a set of qualitative criteria in this section to compare our work with other related works. These criteria include:

Criterion 1 - Integration of three techniques of TL: whether they proposed the use of instance-based, feature-based, and parameter-base TL to improve the knowledge models.

Criterion 2 - TL for insect pests: whether they consider knowledge models related to insect pests such as boll weevil.

Criterion 3 - Climate data: whether they considered the climate data using structured data.

Criterion 4 - TL for prediction model: whether they propose a TL approach for prediction models.

Criterion 5 - Adaptability: whether the proposal can be applied to other knowledge models in other fields.

According to the above criteria, Table 12 shows the comparison with the related works. The existing works did not meet all the requirements. All the criteria were considered in our work because they allow improving the accuracy of the predictive models implemented in previous works.

Table 12. Qualitative comparison with other works.

Criteria	[1]	[2]	[3]	[4]	Our work
Integration of three techniques of TL					✓
TL for insect pests					✓
Climate data					✓
Prediction model integration with TL	✓	✓	✓	✓	✓
Adaptability	✓	✓	✓	✓	✓

Abbreviations: [1] Thenmozhi & Srinivasulu Reddy (2019), [2] Meena et al. (2023), [3] Hadipour-Rokni et al., 2023), [4] Coulibaly et al. (2022).

Some works have used TL techniques to improve the performance of machine learning algorithms by transferring knowledge from one domain to another. For example, TL techniques have been used to improve the classification of insect pests in several crops (Coulibaly et al., 2022; Hadipour-Rokni et al., 2023; Meena et al., 2023; Thenmozhi & Srinivasulu Reddy, 2019). These works used a feature-based TL approach to improve the quality of the models in the target domains. In general, the benefits reflect increased accuracy, efficiency, and the use of pre-trained models that could be used in similar applications to save time and computational resources. However, none of these works includes the study of three TL techniques to improve the machine-learning models. This integration facilitates the identification of the TL technique that leads to enhanced performance in the target domain. In addition, our proposal includes climatic data to determine the behavior of the boll weevil, which is not usually considered. Also, the prediction model was integrated with TL and can be adapted to other scenarios or application domains.

Finally, some works applied TL techniques on structured data to improve results when there is little data. Thus, three works used instance-based TL (Chowdhury et al., 2021; Wang & Yang, 2021; Zhang et al., 2020). Four works used feature-based TL with structured data

(Jung et al., 2021; Qing et al., 2015; Zhao et al., 2017; Zhong et al., 2018). Unlike previous works, our approach used three techniques of TL (instance-, feature-, and parameter-based TL), which represents an improvement with respect to previous works. Our approach is more flexible and adaptable to different scenarios and domains, by allowing us to select, transform and adjust the most relevant instances, features and/or parameters from the source domain to the destination domain, as required by the context of the problem. This improves the accuracy and robustness of the models, by reducing the risk of negative transfers, overfitting, or underfitting, by enhancing the generalization and representation capabilities of the models, as can be seen in Table 13, where very good results were obtained with our approach for the different types of TL.

Table 13. Quantitative comparison with other works.

Work	Instance	Feature	Parameter
	Accuracy	Accuracy	Accuracy
Zhang et al., 2020	90.68%	NU	NU
Wang & Yang, 2021	80%	NU	NU
Chowdhury et al., 2021	95.62%	NU	NU
Zhao et al., 2017	NU	84%	NU
Qing et al., 2015	NU	81.8%	NU
Jung et al., 2021	NU	97.9%	NU
Zhong et al., 2018	NU	81.13%	NU
Our	90.79%	96.28%	79.2%

Abbreviation: NU= Not used.

7. Conclusions

This study aimed to investigate the use of TL techniques to improve the classification of boll-weevil populations by incorporating climate variables as features. Three types of TL techniques, instance-based, feature-based, and parameter-based, were employed to improve the classification performance of the XGBoost algorithm. The study used data from two domains, one with few instances and the other with few features, to test the proposed approach.

Particularly, the study demonstrates the potential of the different TL types to overcome the limitations of the availability of data or features, which are common challenges in data analysis in many domains. TL can leverage the existing knowledge from related domains to enhance the learning performance in new domains, thus reducing the need for costly and time-consuming data collection. On the other hand, the TL approaches studied in this work can be applied to other classification problems similar to the one studied in this work, where there are cases with enough structured data from which good models can be built, and other cases with little data or characteristics. The application domains can be very different, from agricultural to medical and industrial fields.

Specifically, the results of this study have important implications for the development and implementation of climate-smart pest management strategies for cotton crops and can be adapted to other crops. Climate-smart pest management reduces pest-induced crop losses, enhances ecosystem services, reduces the greenhouse gas emissions intensity per unit of food produced, and strengthens the resilience of agricultural systems in the face of climate change.

The utilization of TL techniques to improve the classification of boll-weevil populations based on climate variables is useful for monitoring and predicting pest dynamics and risks in different regions and seasons.

The proposed approach achieved significant improvements in classification accuracy for both a few-instance domain and a few-feature domain. The target domain with few instances reached an accuracy of 90.79%, while the target domain with few features reached an accuracy of 96.28%. The highest accuracies were found with the 95% similarity threshold. In addition, parameter-based TL experiments were performed. The tests showed that the target domain improved accuracy. The results demonstrate the effectiveness of TL techniques in improving the classification of boll-weevil populations in cotton crops when few data and characteristics exist.

Our models were tested with metrics such as Accuracy, F1 score, and Student's t-test for the estimation of the quality of the prediction; however, other metrics could be added. In this sense, in future works, it would be interesting to test with other metrics, in order to test the sensibility of our approach. Also, we plan to add other cities with more instances, and test the cases where it failed by oversample. In addition, we plan to merge the work done here with previous research on autonomous cycles in integrated cotton crop management. Finally, we would like to use TL techniques to enhance learning in the application of metacognitive functions in a metacognitive architecture for agriculture.

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Conflicts of Interest

The authors declare there are no conflicts of interest.

Ethical Approval

Not applicable

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