Deep Hybrid Bagging Ensembles for Classifying Histopathological Breast Cancer Images

Fatima-Zahrae Nakach[1], Ali Idri[1,2] and Hasnae Zerouaoui[1]
[1]*Modeling, Simulation and Data Analysis, Mohammed VI Polytechnic University, Marrakech-Rhamna, Benguerir, Morocco*
[2]*Software Project Management Research Team, ENSIAS, Mohammed V University, Rabat-Salé-Kénitra, Rabat, Morocco*

Keywords: Ensemble Learning, Bagging, Transfer Learning, Breast Cancer.

Abstract: This paper proposes the use of transfer learning and ensemble learning for binary classification of breast cancer histological images over the four magnification factors of the BreakHis dataset: 40×, 100×, 200× and 400×. The proposed bagging ensembles are implemented using a set of hybrid architectures that combine pre-trained deep learning techniques for feature extraction with machine learning classifiers as base learners (MLP, SVM and KNN). The study evaluated and compared: (1) bagging ensembles with their base learners, (2) bagging ensembles with a different number of base learners (3, 5, 7 and 9), (3) single classifiers with the best bagging ensembles, and (4) best bagging ensembles of each feature extractor and magnification factor. The best cluster of the outperforming models was chosen using the Scott Knott (SK) statistical test, and the top models were ranked using the Borda Count voting system. The best bagging ensemble achieved a mean accuracy value of 93.98%, and was constructed using 3 base learners, 200× as a magnification factor, MLP as a classifier, and DenseNet201 as a feature extractor. The results demonstrated that bagging hybrid deep learning is an effective and a promising approach for the automatic classification of histopathological breast cancer images.

1 INTRODUCTION

Breast cancer (BC) became the most commonly diagnosed cancer type in the world in 2021, impacting more than 2.1 million women and causing more than one million deaths per year (Sung et al. 2021). The early detecting and accurate diagnosis of BC can improve the survival rate of BC patients (Clegg et al. 2009). Histopathology biopsy imaging is currently the gold standard for identifying BC in clinical practice since it provides a comprehensive view of how the malignancy affects the tissues (Kumar et al. 2017). However, it is difficult to categorize some intricate visual patterns as benign or malignant in the histopathology slides (Gupta and Bhavsar 2017). Machine learning (ML) models can assist pathologists for automatic cancer disease detection by improving the accuracy and speeding up the diagnosis process (din et al. 2022). The identification of the tumor type is a necessary step before a patient can be given a better treatment plan that increases their chance of survival, that is why ML models have to initially distinguish benign from malignant tumors (Kumar et al. 2017). Several ML classifiers have been applied in cancer research for the development of predictive models (Saxena and Gyanchandani 2020), but none of them has been proved to always outperform the others (Zerouaoui and Idri 2021; Nemade et al. 2022).

To avoid making a poor predictive decision based on a single selected model (Shen et al. 2020), ensemble learning aims to improve the performance of one algorithm by using an intelligent combination of several individual models (also called base learners) and reducing both variance and bias (Tuv 2006). In fact, previous research has shown that an ensemble is often more accurate than any of the base learners (Hastie et al. 2009). However, it must be considered that in some cases the best individual classification model within the ensemble might beat the performance of its ensemble (Polikar 2012). Bagging is an ensemble learning method based on the aggregation of the decision of different predictors that were parallelly trained on different random subsets of the dataset using the same ML algorithm (Breiman 1996).

To address the BC binary classification of histopathological images, researchers have used different ensemble techniques that outperform single

Nakach, F., Idri, A. and Zerouaoui, H.
Deep Hybrid Bagging Ensembles for Classifying Histopathological Breast Cancer Images.
DOI: 10.5220/0011704200003393
In *Proceedings of the 15th International Conference on Agents and Artificial Intelligence (ICAART 2023) - Volume 2*, pages 289-300
ISBN: 978-989-758-623-1; ISSN: 2184-433X

classifiers (Abdar and Makarenkov 2019; Abdar et al. 2020; Hameed et al. 2020; Nakach et al. 2022a; Alaoui et al. 2022; Abbasniya et al. 2022). For bagging ensembles, the majority of papers are classifying the tumors using tabular data: (Nascimento et al. 2011; Wang et al. 2018; Naveen et al. 2019; Sharma and Deshpande 2021), BC mammography images (Ponnaganti and Anitha 2022) (Lbachir et al. 2021) and gene expression (Otoom et al. 2015; Wu and Hicks 2021) or they are using the bagging ensemble to compare it with the performance of another proposed method (Yadavendra and Chand 2020). For histopathological images, this paper (Zhang et al. 2013) used traditional ML classifiers with bagging as Support Vector Machine (SVM), Multilayer Perceptron (MLP), and Decision Trees (DT) without CNNs and without varying the number of base learners. On the other hand, the papers that used a hybrid architecture only used DT as a base learner (Guo et al. 2018) (Nakach et al. 2022b).

In order to confirm or refute the usefulness of bagging ensembles in diagnosing BC in comparison with single ML classifiers, the present study develops and evaluates a set of bagging hybrid architecture ensembles for binary classification of BC histopathological images over the BreakHis dataset at different magnification factors (MFs): 40×, 100×, 200×, and 400×. The forty-eight bagging ensembles are designed using: (1) three of the most recent DL techniques for feature extraction using transfer learning: DenseNet201, MobileNetV2, and InceptionV3, (2) three of the most popular ML classifiers as base learners: MLP, K-Nearest Neighbours (KNN), and SVM, and (3) different number of base learners (3, 5, 7 and 9 estimators).

The main objective is to look into the effect of the type and number of base learners on the predictive capability of the bagging ensembles, and to examine the impact of various feature extraction DL models on the performance of the bagging ensembles. For that purpose, four research questions (RQs) are explored in this study:

• (RQ1). Do Bagging Ensembles Outperform their base Learners?

• (RQ2). How the Number of base Learners Impacts the Performance of Bagging Ensembles?

• (RQ3). Do Bagging Ensembles Outperform Their Single Classifiers?

• (RQ4). Is There any Bagging Ensemble that Outperforms the Others for Each MF and Over all the MFs?

The rest of the paper is as follows. A summary of related work is given in Section 2. Section 3 presents data preparation and the empirical methodology followed throughout the research. Section 4 reports the empirical findings and discussions. Section 5 highlights the conclusion and future direction of this study.

2 RELATED WORK

This section presents an overview of primary studies investigating ensemble learning for BC histopathological image classification. Kassani et al. (Kassani et al. 2019) created a bagging ensemble with pre-trained CNNs: MobileNetV2, VGG19 and DenseNet201 for automatic binary classification of breast histopathological images, the results proved that the best single classifier is DenseNet201 and that the proposed multi-model ensemble method obtains better predictions than single classifiers of VGG19, MobileNetV2, and DenseNet201. Additionally, the proposed ensemble outperforms ML algorithms (DT, Random Forest, XGBoost, AdaBoost and Bagging Classifier) with an accuracy of 98.13%, for BreakHis dataset (MF independent). For ML algorithms and the BreakHis dataset, the topmost result was obtained by: the bagging ensemble with 94.97% accuracy, XGBoost with an accuracy of 94.11%, followed by Random Forest with an accuracy of 92.10%, and AdaBoost with an accuracy of 91.82%.

In another study (Zhu et al. 2019), the bagging ensembles were constructed using hybrid CNN models to classify the BreakHis dataset with its 4 MFs and the BACH dataset. The results showed that combining multiple compact CNNs led to an improvement in classification performance, with an accuracy of 85.7%, 84.2%, 84.9% and 80.1% for MF 40×, 100×, 200× and 400× respectively.

Additionally, Wang et al. (Wang et al. 2020) designed a bagging DT ensemble and a subspace discriminant classifiers ensemble to classify the images of the BreakHis dataset, the DT bagging ensemble achieved the highest accuracy rate of 89.7% compared to the single classifiers. For multi-classification, the subspace discriminant classifier ensemble gave the accuracy of 88.1%. Moreover, in (Alaoui et al. 2022), deep stacked ensembles were developed using seven pre-trained deep learning (DL) models: VGG16, VGG19, ResNet 50, InceptionV3, Inception ResNet V2, Xception, and MobileNet V2, then a logistic regression was used as a meta-learner that learns how to best combine the predictions of the DL models. The results showed that the proposed deep stacking ensemble reports an overall accuracy of 93.8%, 93.0%, 93.3%, and 91.8% over the four MF values of the BreakHis dataset: 40×, 100×, 200× and 400×, respectively.

3 MATERIALS AND METHODS

This section presents: the publicly available dataset used in the empirical evaluations carried out in this study, the different performance criteria used to evaluate the models, the experimental process and the abbreviations.

3.1 Data Preparation

In this paper the Breast Cancer Histopathological Image Classification (BreakHis) dataset (Spanhol et al. 2016) is used in order to examine the viability of the hybrid bagging ensembles. Before feeding the input images into the proposed models, the pre-processing is a crucial step which aims to improve the quality of their visual information. In this study, the preprocessing step is similar to the process that has been followed in (Zerouaoui et al. 2021) and (Zerouaoui and Idri 2022) where they used intensity normalization (B 2019) and Contrast Limited Adaptive Histogram Equalization (CLAHE) (Yussof 2013). After the pre-processing step, data augmentation (Shorten and Khoshgoftaar 2019) was used to avoid overfitting and balance the data by increasing the number of benign images.

3.2 Performance Measures

The performance criteria used to evaluate bagging ensembles as well as their base learners and single models are: accuracy, precision, sensitivity and F1-score. These metrics have been the most frequently used in classification (Zerouaoui and Idri 2021) and they are mathematically expressed by the equations 1-4 respectively:

$$Accuracy=(TP+TN)/(TN+TP+FP+FN) \quad (1)$$

$$Precision=TP/(TP+FP) \quad (2)$$

$$Sensitivity =TP/(TP+FN) \quad (3)$$

$$F1\text{-}score=2\times(Recall\times precision)/(Recall+precision) \quad (4)$$

where: TP is a malignant case that is identified as malignant, FP is a benign case that is identified as malignant, TN is a benign case that is identified as benign, and FN is a malignant case that is identified as benign.

3.3 Experimental Process

The empirical evaluations of the hybrid bagging ensembles use three classifiers: MLP, SVM and KNN, and three DL feature extractors (FE): InceptionV3, DenseNet201, and MobileNetV2, over the four MFs of the BreakHis dataset: 40×, 100×, 200×, and 400×. To compare the models, this study used the SK statistical test (Jelihovschi et al. 2014) based on accuracy to cluster the models and identify the best SK cluster. The best SK cluster contains one or many models that have the best accuracy and that are statistically indifferent. If many models are found, they will be ranked using the Borda Count voting system (Emerson 2013) based on the four performance measures: accuracy, sensitivity, precision and F1-score. The 5-fold cross validation was employed to guarantee that every observation from the original dataset has a chance of appearing in both the training and test set and that the images selected for testing were not used during training in order to successfully complete the binary classification task. The empirical evaluations involve eight steps as shown in Figure 1. The present study has the same potential threats to validity of the approach in this study (Nakach et al. 2022b).

3.4 Abbreviation

The abbreviation of bagging ensembles is EBG, plus the first letter of the classifier used (K for KNN, M for MLP and S for SVM) and the first letter of the FE technique used (D for DenseNet201, I for InceptionV3 and M for MobileNetV2) followed by the number of base learners.

In tables and figures, the DL techniques were abbreviated using: DENSE for DenseNet_201, MOB for MobileNet_V2, and INC for Inception_V3.

4 RESULTS AND DISCUSSIONS

This section presents and discusses the results of the empirical evaluations, where each is dedicated for one RQ.

4.1 Do Bagging Ensembles Perform Better than Their Base Learners?

This section evaluates and compares the bagging ensembles with their base learners. For each MF, FE, and classifier, the bagging ensembles were first compared in terms of accuracy with their base learners. For each MF and FE, it was observed that:

-For KNN and MLP, the accuracy of the bagging ensembles is always better than the mean accuracy of their base learners.

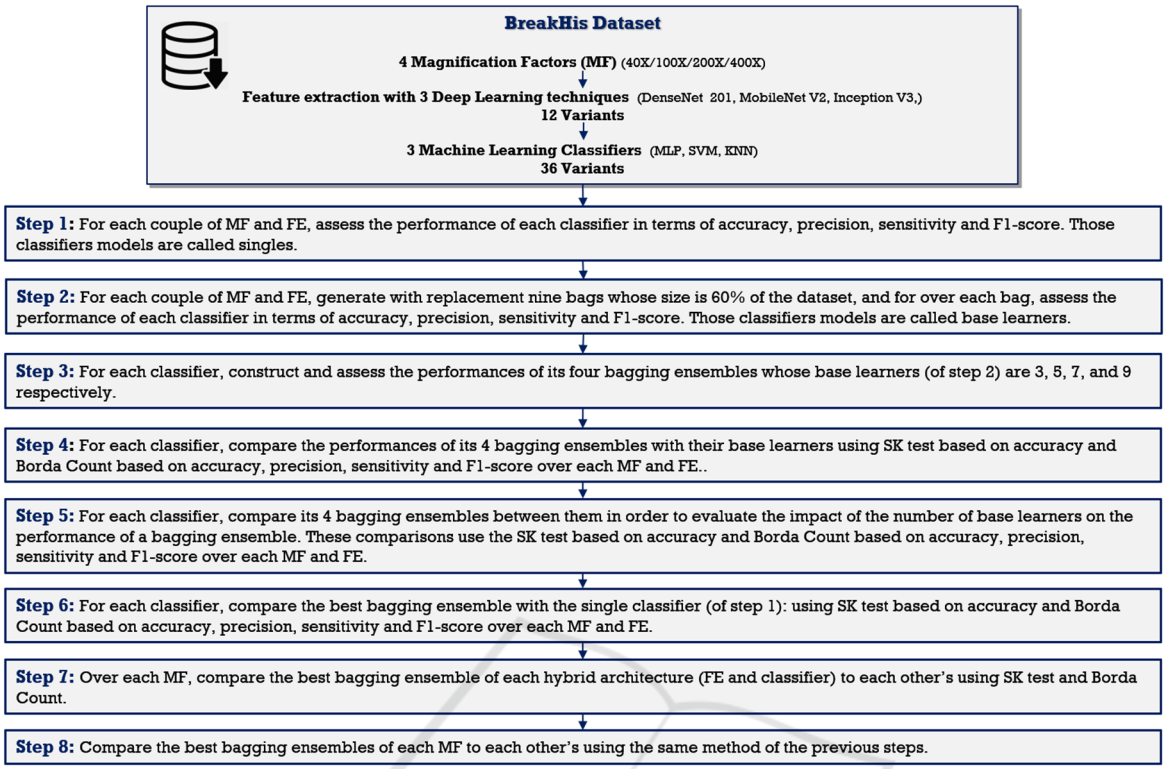


Figure 1: Empirical Design.

- For SVM, the mean accuracy of the base learners outperformed the accuracy of bagging ensembles constructed using: 9 base learners with MobileNetV2 as FE and MF 100× and 400×, 3 and 5 base learners with InceptionV3 as FE and MF 400×. All the other SVM bagging ensembles have a higher accuracy than the mean accuracy of their base learners.

-The difference of accuracies varies between: 13.04% and 4.58% for MLP, 5.85% and 0.56% for KNN, and 1.48% and 0.02% for SVM.

The SK test based on accuracy was carried out over each MF and FE and for each classifier to check whether there was a notable difference between the performance of the bagging ensembles and their base learners. The results showed that:

• For MLP, only one cluster was obtained over each MF and FE except for MF 400× with DenseNet201 and InceptionV3, where the bagging ensembles significantly outperformed one or two of their base learners (Figure 2).

• For SVM, only one cluster was identified over each FE and for MF 100×, 200× and 400×. For MF 40×, always one cluster was obtained except for InceptionV3 as FE, where the bagging ensembles with 7 and 9 base learners outperformed one of their base learners.

• For KNN, only one cluster was obtained over each MF and FE except for: (1) MobileNetV2 as FE and MF 200× where the best cluster contains the bagging ensemble with 3 base learners, and (2) InceptionV3 and MF 400× where the best cluster contains the bagging ensemble with 9 base learners, the second cluster contains all the base learners.

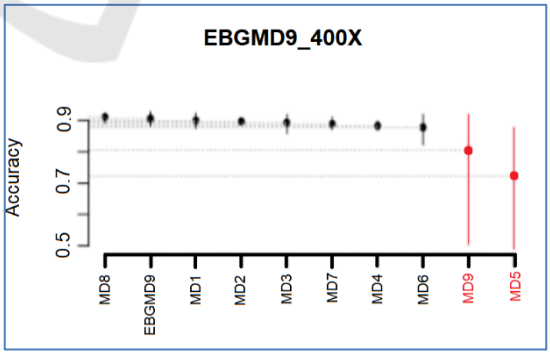


Figure 2: SK test Results of the MLP bagging ensemble using MF 400×, 9 base learners and DenseNet201 as FE.

The models that belong to the same best cluster were ranked using the Borda Count voting system:

• For MLP, the bagging ensemble is generally ranked first whatever the MF and FE are. The bagging

ensemble was ranked second or third for DenseNet201 over MF 40× regardless the number of base learners, and it was ranked second for InceptionV3 over MF 200× with 7 and 9 base learners and with MobileNetV2 over MF 40× for 5 base learners.

• For SVM, the bagging ensembles had the worst ranks (4th, 5th and sometimes 6th) and only 20 ensembles out of 48 were ranked first.

• For KNN, the bagging ensembles are always ranked first except for the bagging ensemble constructed using 7 base learners with KNN and DenseNet201 over the MF 200×.

To conclude, the bagging ensembles outperform their base learners for MLP, KNN, but for SVM, the base learners often perform better than the bagging ensembles. Besides, the differences of accuracies between the MLP bagging ensembles and their base learners were relatively important compared to the differences of accuracies between the SVM and KNN bagging ensembles and their base learners, which was expected since bagging ensembles perform better with base learners that have a high variance such as MLP and DT (Tuv 2006)(Opitz and Maclin 1999). This paper (Nakach et al. 2022b) also found that the bagging ensembles using DT outperform their base learners for each MF).

4.2 How the Number of Base Learners Impacts the Performances of Bagging Ensembles?

Figures 3–5 show the comparison of the accuracy values of the different bagging ensembles over each classifier using the four number of base learners, three DL techniques as FEs (DenseNet201, InceptionV3 and MobileNetV2) and four MF values: 40×, 100×, 200× and 400×.

For the MLP Classifier:

• The highest accuracy was obtained when using the DenseNet201 as FE regardless the MF values: 40×, 100×, 200× and 400×, and the lowest accuracy was obtained using MobileNetV2 for FE.

For the SVM Classifier:

• The highest accuracy was obtained when using the InceptionV3 as FE with the MF value 40× and 400×, and with DenseNet201 with the MF value 100× and 200×. The lowest accuracy was obtained using MobileNetV2 as FE with all MF values.

For the KNN Classifier:

• The highest accuracy was obtained when using the InceptionV3 as FE for the MF 40×, and with DenseNet201 for the MF 100× and 200×, and with MobileNetV2 for MF 400×. The lowest accuracy was obtained when using InceptionV3 regardless the MF values.

Thereafter, the SK statistical test was used to cluster the bagging ensembles with different number of base learners for each classifier, FE and MF. For MLP and SVM, the SK test of the bagging ensembles contains one cluster over each FE and MF, which implies that regardless the number of base learners used the accuracy of the ensembles is statistically similar. For KNN, the SK test identified one cluster with all the bagging ensembles for all the MFs and FEs except for InceptionV3 over the MF 100×, where two clusters were identified and the worst one contains the ensemble of 9 base learners. Table 1 displays the ranking provided by the Borda Count voting system for the bagging ensembles over each classifier, FE and MF: the first number represents the number of base learners associated to the best bagging ensemble.

It was found that regardless the hybrid architecture used, the ensemble of 9 base learners represents the best ensemble for the majority of bagging ensembles (31 from 48) and it was ranked last only 3 times (SVM with MF 40× and InceptionV3 and with MF 100× and MobileNetV2, and for KNN with MF 40× and MobileNetV2). Contrarily, the ensemble of 3 base learners was only ranked twice as the best ensemble and 33 times as the worst one.

The bagging ensemble of 5 and 7 base learners were ranked first 8 and 7 times out of 48 respectively.

Table 1: Borda Count ranking of the bagging ensembles of each classifier.

MF	FE	MLP	SVM	KNN
40×	DENSE	3-9-5-7	9-5-7-3	9-7-5-3
	MOB	9-7-5-3	7-9-5-3	5-7-3-9
	INC	9-7-5-3	7-5-3-9	9-7-5-3
100×	DENSE	9-5-7-3	9-7-3-5	9-5-7-3
	MOB	9-3-7-5	5-7-3-9	9-7-5-3
	INC	7-9-5-3	7-9-5-3	9-7-5-3
200×	DENSE	9-7-3-5	5-3-9-7	3-5-9-7
	MOB	9-5-7-3	9-7-5-3	5-9-3-7
	INC	5-7-9-3	5-9-3-7	9-7-5-3
400×	DENSE	9-7-3-5	9-3-7-5	7-5-9-3
	MOB	9-7-3-5	5-7-9-3	5-9-7-3
	INC	9-7-3-5	9-7-5-3	9-7-5-3

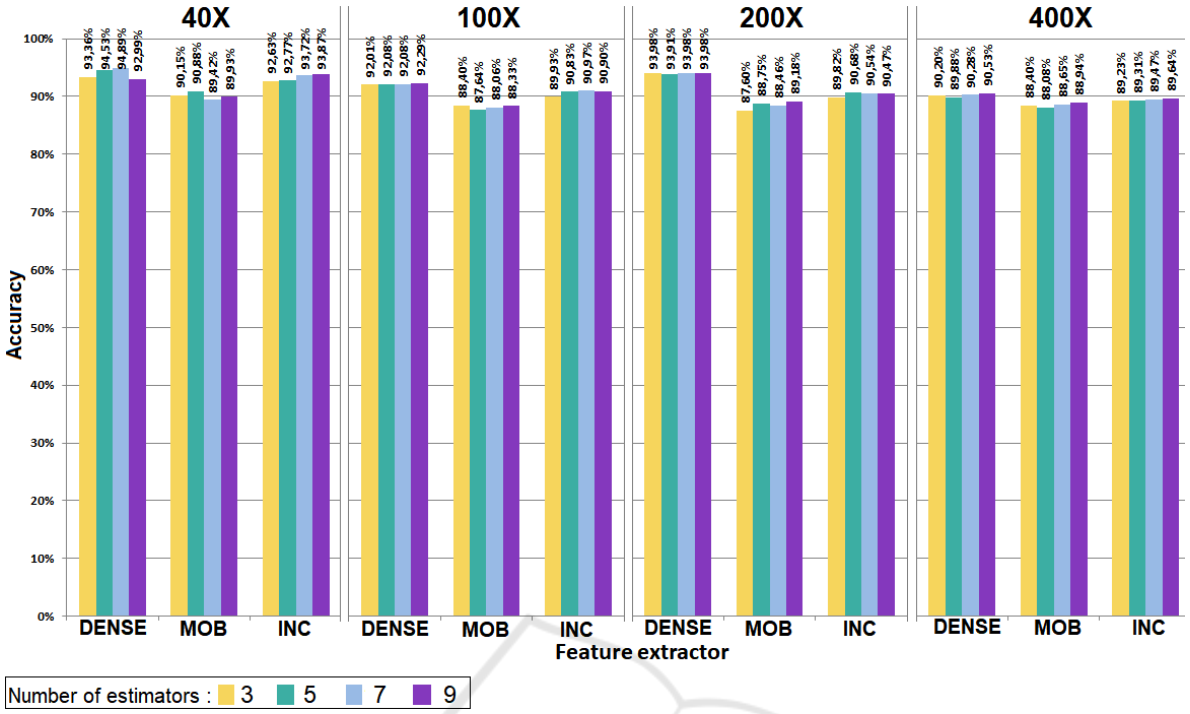


Figure 3: Accuracy values of the bagging ensembles using MLP Classifier over each MF and FE.

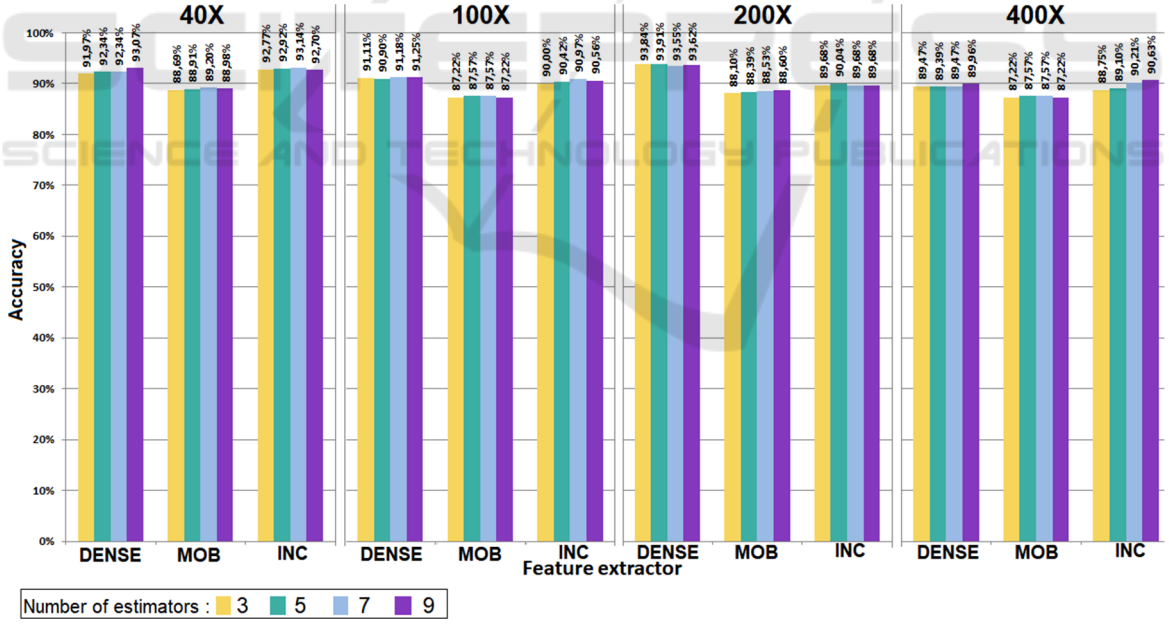


Figure 4: Accuracy values of the bagging ensembles using SVM Classifier over each MF and FE.

It can be concluded that, for the majority of MFs and FEs, the bagging ensembles designed with KNN and MLP and 9 base learners were the best ensemble while those designed with 3 base learners represents the worst ones. For SVM, the bagging ensembles did not seem to respect a specific order.

4.3 Do Bagging Ensembles Perform Better than Single Classifiers?

This section compares the single model and the best bagging ensemble of each classifier. Tables 2-4 summarize the testing accuracy values of the single

model and the best bagging ensemble for each classifier and over each MF and FE (found in section 4.2). It was found that bagging ensembles are performing better than the single classifiers for KNN (they have the highest accuracy), while for SVM and MLP the single classifiers are performing better for some FEs and MFs. For KNN, the difference of accuracies between bagging ensembles is smaller than the difference of accuracies between single models (e.g., for MF 40×, the KNN single model has an accuracy of 83.65% and 64.74% for DenseNet201 and MobileNetV2 respectively, while the bagging KNN ensemble achieves an accuracy of 83.21% and 80.66% for DenseNet201 and MobileNetV2 respectively), which means that the KNN bagging ensembles are more stable than the KNN single models.

In order to identify which model is the best, the models of the best SK cluster of each MF and FE were ranked by using the Borda Count voting system. By comparing the number of occurrences of bagging ensembles and single techniques in the Borda Count rankings results, it was found that single classifiers are the most frequent for MLP (8 from 12) and SVM

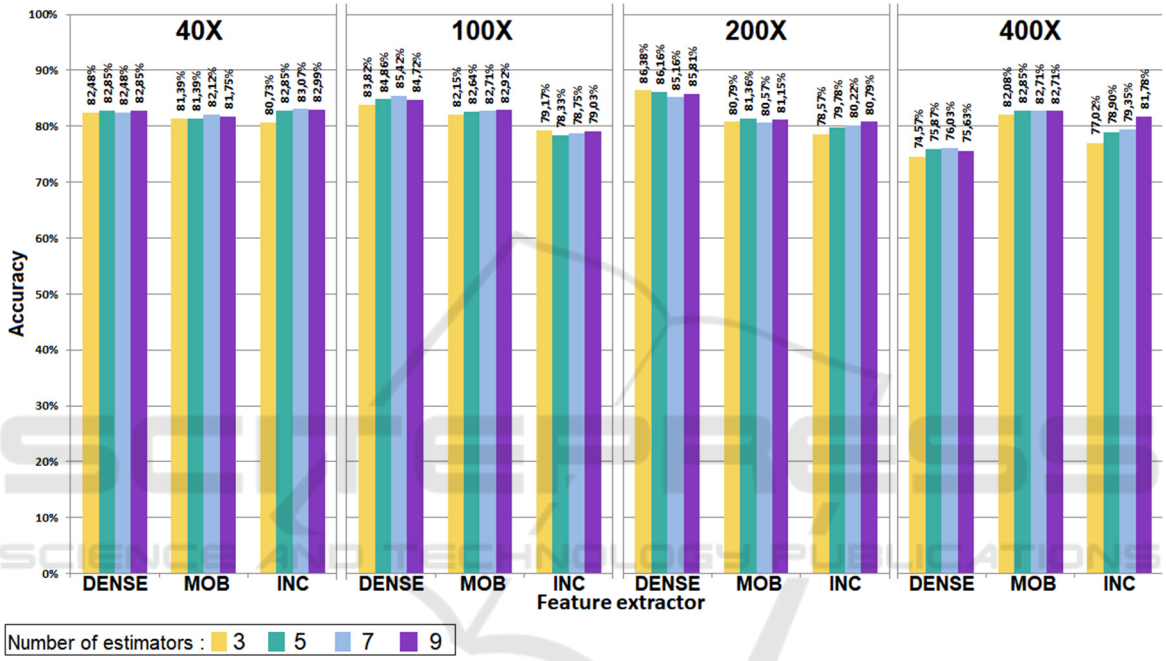


Figure 5: Accuracy values of the bagging ensembles using KNN Classifier over each MF and FE.

Table 2: Performance values of single MLP classifiers and the best MLP bagging ensembles.

		Single classifiers (%)				Best Bagging ensembles (%)			
MF	FE	Accuracy	Precision	Sensitivity	F1-score	Accuracy	Precision	Sensitivity	F1-score
40×	DENSE	93.28	92.21	94.49	93.33	93.36	92.60	94.79	93.66
	INC	92.92	91.30	94.90	93.05	93.87	93.73	94.53	94.11
	MOB	91.06	88.94	93.82	91.30	89.93	88.01	93.41	90.61
100×	DENSE	92.28	91.90	92.80	92.33	92.29	91.10	93.50	92.28
	INC	90.22	88.85	92.25	90.43	90.97	88.09	94.51	91.17
	MOB	91.16	89.20	93.67	91.38	88.33	84.92	92.90	88.70
200×	DENSE	94.84	94.96	94.18	95.78	93.98	92.88	95.49	94.15
	INC	91.76	91.85	91.87	91.94	90.68	90.74	91.01	90.82
	MOB	91.80	90.70	93.24	91.92	89.18	87.04	92.66	89.72
400×	DENSE	83.97	87.09	83.78	93.08	90.53	90.74	90.65	90.61
	INC	90.28	90.49	88.90	92.24	89.64	88.25	91.60	89.90
	MOB	89.77	87.70	92.54	90.05	88.94	85.61	93.62	89.41

Table 3: Performance values of single SVM classifiers and the best SVM bagging ensembles.

		Single classifiers (%)				Best Bagging ensembles (%)			
MF	FE	Accuracy	Precision	Sensitivity	F1-score	Accuracy	Precision	Sensitivity	F1-score
40×	DENSE	92.52	90.98	94.36	92.62	91.61	90.73	93.41	92.02
	INC	92.63	91.23	94.29	92.74	93.14	92.43	94.52	93.45
	MOB	90.18	87.72	93.59	90.52	89.20	86.38	94.14	90.06
100×	DENSE	91.68	90.49	93.23	91.81	91.25	89.36	93.39	91.32
	INC	90.15	87.85	93.27	90.46	90.97	87.74	95.05	91.22
	MOB	90.71	87.75	94.66	91.06	87.57	83.70	92.77	87.98
200×	DENSE	93.60	92.45	94.97	93.68	93.91	93.12	95.08	94.07
	INC	89.75	86.86	93.66	90.13	90.04	88.43	92.56	90.43
	MOB	90.97	88.45	94.33	91.26	88.60	86.43	92.24	89.20
400×	DENSE	91.23	89.64	93.36	91.42	89.96	88.81	91.92	90.27
	INC	88.79	86.30	92.40	89.21	90.63	87.13	95.07	90.91
	MOB	89.16	86.29	93.21	89.59	87.57	83.70	92.77	87.98

Table 4: Performance values of single KNN classifiers and the best KNN bagging ensembles.

		Single classifiers (%)				Best Bagging ensembles (%)			
MF	FE	Accuracy	Precision	Sensitivity	F1-score	Accuracy	Precision	Sensitivity	F1-score
40×	DENSE	83.65	76.28	97.66	85.64	83.21	76.29	98.32	85.89
	INC	82.66	79.05	88.98	83.68	82.99	78.63	92.43	84.96
	MOB	64.74	58.73	99.42	73.82	80.66	73.50	98.31	84.09
100×	DENSE	85.04	79.27	94.95	86.40	84.72	78.60	94.78	85.89
	INC	78.22	72.44	91.25	80.75	79.03	72.99	91.67	81.16
	MOB	69.94	62.74	98.32	76.58	82.92	75.13	97.74	84.90
200×	DENSE	83.42	76.62	96.32	85.33	86.38	80.10	97.61	87.95
	INC	79.50	73.59	92.16	81.81	80.79	74.41	95.00	83.43
	MOB	70.90	63.54	98.27	77.16	81.36	74.35	96.95	84.12
400×	DENSE	80.67	73.95	94.96	83.10	76.03	70.19	91.85	79.53
	INC	77.34	71.66	90.57	80.00	79.92	74.02	93.26	82.51
	MOB	71.13	66.10	86.77	75.00	82.85	75.18	97.19	84.75

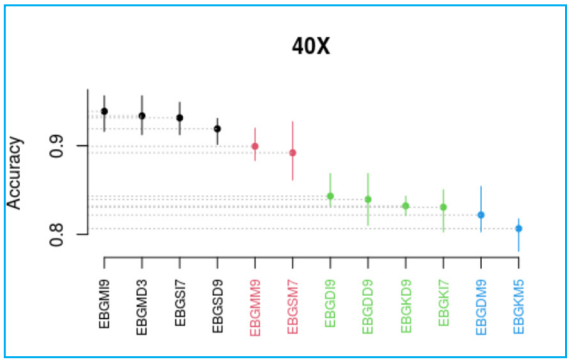
(7 from 12), but for KNN, the bagging ensembles outperformed the single classifiers since 10 bagging ensembles from 12 were ranked first.

In summary, for KNN, the bagging ensembles outperformed the single classifiers for the majority of MFs and FEs. Contrarily, MLP and SVM single classifiers generally performed better than the bagging ensembles. The reason is that MLP and SVM can be considered as strong learners, and their single classifiers significantly perform well compared to the single KNN classifier.

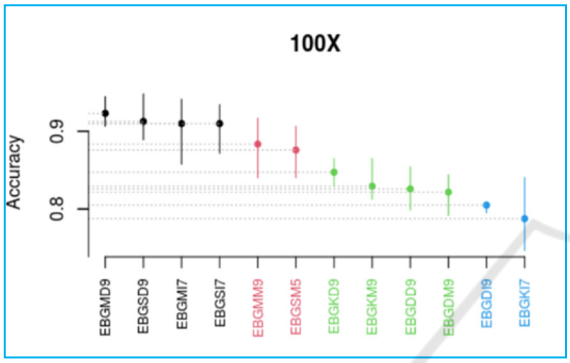
4.4 Is There any Bagging Ensemble that Outperforms the Others for Each MF and over all the MFs?

This section evaluates and compares the best bagging ensembles of each hybrid architecture (FE and classifier) over each MF and the best ensembles over all the MFs. Figure 6 shows the results of SK test for the best bagging ensembles of each hybrid architecture (found in section 4.2) over the four MFs. Different clusters were obtained: four clusters for MF 40×, 100× and 200×, and three clusters for MF 400×. In addition to the classifiers used in the present paper, the bagging ensembles with DT classifier and different FEs developed in this paper (Nakach et al. 2022b) were also added to the comparison (they are abbreviated using "EBGD").

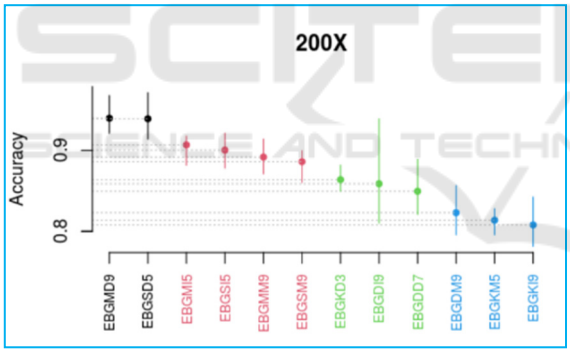
It was found that SVM and MLP with DenseNet201 and InceptionV3 always form the hybrid architecture of the best four bagging ensembles for the different MFs but they don't respect a specific order and they use a different number of base learners. Three



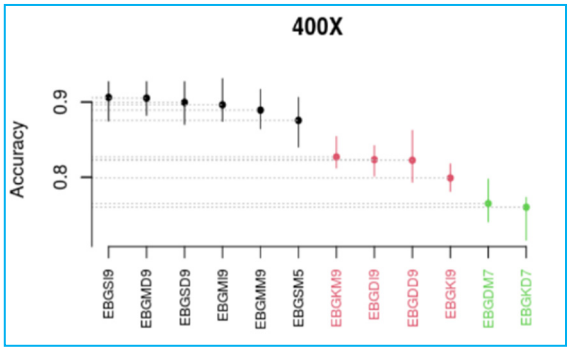
(a)



(b)



(c)



(d)

Figure 6: SK Results of the best bagging ensembles of each classifier and FE over each MF: (a) 40×, (b) 100×, (c) 200×, (d) 400×.

from the four first ranked ensembles were constructed using MLP, and only the best bagging ensemble over MF 400× was constructed with SVM. The majority of those ensembles have 9 base learners (8 from 16) and only 2 ensembles have 3 base learners. For DenseNet201, MLP is ranked first for all the MFs, but for InceptionV3 MLP is ranked first for MF 40× and MF 200× while SVM is ranked first for MF 100× and MF 400×.

The results show that the performance of the different bagging ensembles depends on the characteristic of the images and the bagging ensembles that use MLP and SVM as base learners outperform the bagging ensembles that use KNN and DT as base learners. Figure 7 shows the results of SK test for the best bagging ensembles over the four MFs. Table 5 presents the ranking results of the best bagging ensembles using the Borda count voting to identify the best hybrid architecture regardless of the MF.

To sum up, the bagging ensemble that uses MF 200×, 3 base learners and the hybrid architecture MLP with DenseNet201 as FE was ranked first, the second-best ensemble uses MF 40×, 9 base learners and the base hybrid architecture MLP with InceptionV3 as FE, the third best ensemble is constructed using MF 100×, 9 base learners and uses the base hybrid architecture MLP with DenseNet201 as FE. The bagging ensemble designed with MF 400×, 9 base learners and whose base hybrid architecture is SVM with InceptionV3 as FE was ranked fourth.

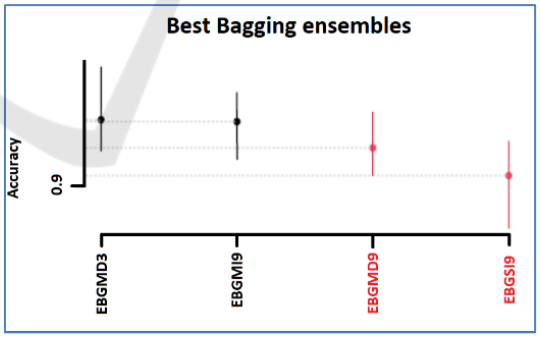


Figure 7: SK test Results of the best bagging ensembles.

In addition, the results obtained in the experimental studies in the literature using the BreakHis dataset for binary classification of the four MFs are presented for comparison purposes in Table 6. It should be taken into account that different training and test sample numbers were used in these studies. The proposed bagging ensembles can produce considerably higher accuracies compared to the state-of-the-art model, they achieve better performance than the candidate

Table 5: Best bagging ensembles over all the MFs.

Model	MF	Accuracy (%)	F1-score (%)	Precision (%)	Sensitivity (%)	Rank
EBGMD3	200×	93,98	94,15	92,88	95,49	**1**
EBGMI9	40×	93,87	94,11	93,73	94,53	**2**
EBGMD9	100×	92,29	92,28	91,10	93,50	**3**
EBGSI9	400×	90,63	90,91	87,13	95,07	**4**

Table 6: Accuracy comparisons between the best bagging ensembles for each MF and the other models on BreakHis.

Method	40× (%)	100× (%)	200× (%)	400× (%)
SIFT + Stacked ensemble [50]	88.5	89.2	88.4	83.6
CNNs + SVM [51]	87.7	88.9	90.1	85.1
CNN [52]	89.6	85.0	82.8	80.2
Hybrid CNN ensemble [39]	85.7	84.2	84.9	80.1
ResNet50 + bagging [38]	92.5	92.0	-	-
InceptionV3+GBT [53]	88.9	90.1	89.1	87.5
InceptionV4+GBT [53]	90.4	92.3	93.7	90.1
ResNetV1152+GBT [53]	92.5	**94.8**	**95.8**	90.5
Variant of AlexNet [54]	**95.0**	91.5	91.8	**95.0**
Our best bagging ensembles	93,9	92,3	94.0	90,6

models, expect for: the best model of the study (Senan et al.) for MF 40× and 400×, and the ResNetV1152+GBT model of the study (Vo et al. 2019) for MF 100× and 200×.

5 CONCLUSIONS

In conclusion, this paper presented and discussed the results of an empirical comparative study of bagging ensembles for BC histopathological image classification. This study used the bagging method with different number of base learners (3, 5, 7 and 9) and twelve hybrid architectures (three classifiers: KNN, MLP and SVM with three DL techniques for feature extraction: DenseNet201, MobileNetV2 and InceptionV3) over the BreakHis dataset with its four MFs (40×, 100×, 200× and 400×). The main findings of this study are:

RQ1. Do Bagging Ensembles Perform Better than Their base Learners?
Bagging ensembles outperform their base learners for MLP and KNN, but for SVM, the base learners often perform better than the bagging ensembles.

RQ2. How the Number of Base Learners Impacts the Performances of Bagging Ensembles?
For the majority of MF and FE, the bagging ensembles designed with KNN and MLP respects an ascending order where the bagging ensemble of 9 base learners represents the best ensemble and the ensemble of 3 base learners represents the worst one.

RQ3. Do Bagging Ensembles Perform Better than Single Classifiers?
For KNN, the bagging ensembles outperform the single KNN classifiers for the majority of MF and FE. Contrarily, MLP and SVM single classifiers generally perform better than the bagging ensembles.

RQ4. Is There Any Bagging Ensemble that Outperforms the Others for Each MF And Over all the MFs?
The best bagging ensemble is designed using MF 200×, MLP as a classifier and DenseNet 201 as FE and it has 3 base learners.

In conclusion, the proposed bagging ensembles achieved promising results that can outperform state-of-the-art models. Hence, this paper suggests that bagging with hybrid DL architectures should be considered for BC image classification. In a future work, in order to deepen this analysis, it is possible to implement heterogeneous ensemble learning methods to classify BC histopathological images and compare their performance with the bagging ensembles implemented in this study.

REFERENCES

Abbasniya MR, Sheikholeslamzadeh SA, Nasiri H, Emami S (2022) Classification of Breast Tumors Based on Histopathology Images Using Deep Features and Ensemble of Gradient Boosting Methods. Computers and Electrical Engineering 103:108382. https://doi.org/10.1016/j.compeleceng.2022.108382

Abdar M, Makarenkov V (2019) CWV-BANN-SVM ensemble learning classifier for an accurate diagnosis of breast cancer. Measurement 146:557–570. https://doi.org/10.1016/j.measurement.2019.05.022

Abdar M, Zomorodi-Moghadam M, Zhou X, et al (2020) A new nested ensemble technique for automated diagnosis of breast cancer. Pattern Recognition Letters 132:123–131. https://doi.org/10.1016/j.patrec.2018.11.004

Alaoui O, Zerouaoui H, Idri A (2022) Deep Stacked Ensemble for Breast Cancer Diagnosis. pp 435–445

B N (2019) Image Data Pre-Processing for Neural Networks. In: Medium. https://becominghuman.ai/image-data-pre-processing-for-neural-networks-498289068258. Accessed 12 May 2021

Breiman L (1996) Bagging predictors. Mach Learn 24:123–140. https://doi.org/10.1007/BF00058655

Clegg LX, Reichman ME, Miller BA, et al (2009) Impact of socioeconomic status on cancer incidence and stage at diagnosis: selected findings from the surveillance, epidemiology, and end results: National Longitudinal Mortality Study. Cancer Causes Control 20:417–435. https://doi.org/10.1007/s10552-008-9256-0

din NM ud, Dar RA, Rasool M, Assad A (2022) Breast cancer detection using deep learning: Datasets, methods, and challenges ahead. Computers in Biology and Medicine 149:106073. https://doi.org/10.1016/j.compbiomed.2022.106073

Emerson P (2013) The original Borda count and partial voting. Soc Choice Welf 40:353–358. https://doi.org/10.1007/s00355-011-0603-9

Guo Y, Hui D, Song F, et al (2018) Breast Cancer Histology Image Classification Based on Deep Neural Networks. pp 827–836

Gupta V, Bhavsar A (2017) Breast Cancer Histopathological Image Classification: Is Magnification Important? In: 2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). IEEE, Honolulu, HI, USA, pp 769–776

Güzel K, BiLgiN G (2020) Classification of Breast Cancer Images Using Ensembles of Transfer Learning. Sakarya University Journal of Science. https://doi.org/10.16984/saufenbilder.720693

Hameed Z, Zahia S, Garcia-Zapirain B, et al (2020) Breast Cancer Histopathology Image Classification Using an Ensemble of Deep Learning Models. Sensors 20:4373. https://doi.org/10.3390/s20164373

Hastie T, Tibshirani R, Friedman J (2009) Ensemble Learning. In: Hastie T, Tibshirani R, Friedman J (eds) The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer, New York, NY, pp 605–624

Jelihovschi E, Faria JC, Allaman IB (2014) ScottKnott: A Package for Performing the Scott-Knott Clustering Algorithm in R. Tend Mat Apl Comput 15:003. https://doi.org/10.5540/tema.2014.015.01.0003

Kassani SH, Kassani PH, Wesolowski MJ, et al (2019) Classification of Histopathological Biopsy Images Using Ensemble of Deep Learning Networks. arXiv:190911870 [cs, eess]

Kumar V, Abbas AK, Aster JC (2017) Robbins Basic Pathology E-Book. Elsevier Health Sciences

Lbachir IA, Daoudi I, Tallal S (2021) Automatic computer-aided diagnosis system for mass detection and classification in mammography. Multimed Tools Appl 80:9493–9525. https://doi.org/10.1007/s11042-020-09991-3

Nakach F-Z, Zerouaoui H, Idri A (2022a) Deep Hybrid AdaBoost Ensembles for Histopathological Breast Cancer Classification. In: Rocha A, Adeli H, Dzemyda G, Moreira F (eds) Information Systems and Technologies. Springer International Publishing, Cham, pp 446–455

Nakach F-Z, Zerouaoui H, Idri A (2022b) Random Forest Based Deep Hybrid Architecture for Histopathological Breast Cancer Images Classification. pp 3–18

Nascimento DSC, Canuto AMP, Silva LMM, Coelho ALV (2011) Combining different ways to generate diversity in bagging models: An evolutionary approach. In: The 2011 International Joint Conference on Neural Networks. pp 2235–2242

Naveen, Sharma RK, Ramachandran Nair A (2019) Efficient Breast Cancer Prediction Using Ensemble Machine Learning Models. In: 2019 4th International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT). IEEE, Bangalore, India, pp 100–104

Nemade V, Pathak S, Dubey A, Barhate D (2022) A Review and Computational Analysis of Breast Cancer Using Different Machine Learning Techniques. https://doi.org/10.46338/ijetae0322_13

Opitz D, Maclin R (1999) Popular Ensemble Methods: An Empirical Study. jair 11:169–198. https://doi.org/10.1613/jair.614

Otoom AF, Abdallah EE, Hammad M (2015) Breast Cancer Classification: Comparative Performance Analysis of Image Shape-Based Features and Microarray Gene Expression Data. IJBSBT 7:37–46. https://doi.org/10.14257/ijbsbt.2015.7.2.04

Polikar R (2012) Ensemble Learning. In: Zhang C, Ma Y (eds) Ensemble Machine Learning: Methods and Applications. Springer US, Boston, MA, pp 1–34

Ponnaganti ND, Anitha R (2022) A Novel Ensemble Bagging Classification Method for Breast Cancer Classification Using Machine Learning Techniques. TS 39:229–237. https://doi.org/10.18280/ts.390123

Saxena S, Gyanchandani M (2020) Machine Learning Methods for Computer-Aided Breast Cancer Diagnosis Using Histopathology: A Narrative Review. Journal of

Medical Imaging and Radiation Sciences 51:182–193. https://doi.org/10.1016/j.jmir.2019.11.001

Senan EM, Alsaade FW, Ahmed MI Classification of Histopathological Images for Early Detection of Breast Cancer Using Deep Learning. 24:7

Sharma S, Deshpande S (2021) Breast Cancer Classification Using Machine Learning Algorithms. In: Joshi A, Khosravy M, Gupta N (eds) Machine Learning for Predictive Analysis. Springer, Singapore, pp 571–578

Shen S, Sadoughi M, Li M, et al (2020) Deep convolutional neural networks with ensemble learning and transfer learning for capacity estimation of lithium-ion batteries. Applied Energy 260:114296. https://doi.org/10.1016/j.apenergy.2019.114296

Shorten C, Khoshgoftaar TM (2019) A survey on Image Data Augmentation for Deep Learning. Journal of Big Data 6:60. https://doi.org/10.1186/s40537-019-0197-0

Spanhol FA, Oliveira LS, Petitjean C, Heutte L (2016) A Dataset for Breast Cancer Histopathological Image Classification. IEEE Transactions on Biomedical Engineering 63:1455–1462. https://doi.org/10.1109/TBME.2015.2496264

Sung H, Ferlay J, Siegel RL, et al (2021) Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries. CA: A Cancer Journal for Clinicians 71:209–249. https://doi.org/10.3322/caac.21660

Tuv E (2006) Ensemble Learning. In: Guyon I, Nikravesh M, Gunn S, Zadeh LA (eds) Feature Extraction: Foundations and Applications. Springer, Berlin, Heidelberg, pp 187–204

Vo DM, Nguyen N-Q, Lee S-W (2019) Classification of breast cancer histology images using incremental boosting convolution networks. Information Sciences 482:123–138. https://doi.org/10.1016/j.ins.2018.12.089

Wang H, Zheng B, Yoon SW, Ko HS (2018) A support vector machine-based ensemble algorithm for breast cancer diagnosis. European Journal of Operational Research 267:687–699. https://doi.org/10.1016/j.ejor.2017.12.001

Wang J, Zhu T, Liang S, et al (2020) Binary and Multiclass Classification of Histopathological Images Using Machine Learning Techniques. Journal of Medical Imaging and Health Informatics 10:2252–2258. https://doi.org/10.1166/jmihi.2020.3124

Wu J, Hicks C (2021) Breast Cancer Type Classification Using Machine Learning. Journal of Personalized Medicine 11:61. https://doi.org/10.3390/jpm11020061

Yadavendra, Chand S (2020) A comparative study of breast cancer tumor classification by classical machine learning methods and deep learning method. Machine Vision and Applications 31:46. https://doi.org/10.1007/s00138-020-01094-1

Yussof W (2013) Performing Contrast Limited Adaptive Histogram Equalization Technique on Combined Color Models for Underwater Image Enhancement

Zerouaoui H, Idri A (2021) Reviewing Machine Learning and Image Processing Based Decision-Making Systems for Breast Cancer Imaging. J Med Syst 45:8. https://doi.org/10.1007/s10916-020-01689-1

Zerouaoui H, Idri A (2022) Deep hybrid architectures for binary classification of medical breast cancer images. Biomedical Signal Processing and Control 71:103226. https://doi.org/10.1016/j.bspc.2021.103226

Zerouaoui H, Idri A, Nakach FZ, Hadri RE (2021) Breast Fine Needle Cytological Classification Using Deep Hybrid Architectures. In: Gervasi O, Murgante B, Misra S, et al. (eds) Computational Science and Its Applications – ICCSA 2021. Springer International Publishing, Cham, pp 186–202

Zhang Y, Zhang B, Coenen F, Lu W (2013) Breast cancer diagnosis from biopsy images with highly reliable random subspace classifier ensembles. Machine Vision and Applications 24:1405–1420. https://doi.org/10.1007/s00138-012-0459-8

Zhu C, Song F, Wang Y, et al (2019) Breast cancer histopathology image classification through assembling multiple compact CNNs. BMC Med Inform Decis Mak 19:198. https://doi.org/10.1186/s12911-019-0913-x.