Optimization and Learning Rate Influence on Breast Cancer Image Classification

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Abstract: Breast cancer is a prevalent and challenging pathology, with significant mortality rates, affecting both women and men. Despite advancements in technology, such as Computer-Aided Diagnosis (CAD) and awareness campaigns, timely and accurate diagnosis remains a crucial issue. This study investigates the performance of Convolutional Neural Networks (CNNs) in predicting and supporting breast cancer diagnosis, considering BreakHis and Biglycan datasets. Through a factorial partial method, we measured the impact of optimization and learning rate factors on the prediction model accuracy. By measuring each factor's level of influence on the validation accuracy response variable, this paper brings valuable insights into the relevance analyses and CNN behavior. Furthermore, the study sheds light on the explainability of Artificial Intelligence (AI) through factorial partial performance evaluation design. Among the results, we determine which and how much the hyperparameters tunning influenced the performance of the models. The findings contribute to image-based medical diagnosis field, fostering the integration of computational and machine learning approaches to enhance breast cancer diagnosis and treatment.

1 INTRODUCTION

Although the cancer mortality rate is declining (Benhammou et al., 2020), it represents the greatest barrier to increasing life expectancy (Sahu et al., 2023), especially for women, where breast cancer accounts for 30% of the incidence (Clement et al., 2022). Breast cancer is a pathology caused by the uncontrolled spread of abnormal cells in the breast (dysplasia), causing tumors that can invade other organs (Benhammou et al., 2020). Although rare, breast cancer can also occur in men with about 1% of cases (Alqahtani et al., 2022).

Despite the advancement of technology concerning the treatment and diagnosis of breast cancer and annual incentives with campaigns to carry out exams, this pathology remains a major problem in our soci-

ety, being the most prevalent type of cancer in women and and second in men (Batra et al., 2020)(Sahu et al., 2023). Conventional exams require the careful analysis by a pathologist, consequently resulting in long waiting periods from the exam to scheduling the next appointment to present the diagnosis, considering all procedures performed by the Brazilian Unified Health System (SUS). Time is crucial for the patient as there is a continuous proliferation of abnormal cells (INCA, 2021).

Furthermore, the analysis of images by the pathologist is prone to error due to eye fatigue, human error, and device-dependent influences, which hinders such diagnoses. Therefore, pathologists rely on Computer-Aided Diagnosis (CAD) to assist in the task of identifying and classifying problematic tissues using computational resources in this task (Benhammou et al., 2020)(Yu et al., 2023)(Sahu et al., 2023).

To achieve this, in addition to improving CAD methods, it is important to evolve machine learning techniques to increase the accuracy rate of such diagnoses (Backes, 2022)(Rodrigues Moreira et al., 2023)(Gautam, 2023). Therefore, this paper proposes

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to evaluate the performance of computational techniques for predicting and supporting the diagnosis of breast cancer using two relevant datasets. To accomplish this task, we employed the partial factorial method and carried out experiments to measure the impact of two factors (optimization and learning rate) and their levels (0.001 and 0.0001) on the validation accuracy response variable. This method enables us to identify which factor is more relevant to the validation accuracy variable, shedding light on issues of interpretability of Convolutional Neural Network (CNN) models and their behavior, as well as indicating which factors are more promising in terms of hyperparameter optimization techniques.

The main contribution of this paper is the measurement of the impact of each factor, optimization and learning rate, individually and in combination, on the training accuracy result of the models. In addition, the use of different datasets, such as BreakHis and Biglycan, contributes to a greater generalization of the results, as we are not restricted to just one type of image or context. Also, this study aims to shed light on explaining Artificial Intelligence (AI) through factorial partial performance evaluation. Finally, this study contributes to the area of image-based medical diagnosis, using computational and machine-learning approaches.

The remaining sections of this paper are organized as follows: Section 2 provides an overview of related works in the literature that are similar to the proposed approach. Section 3 presents the proposed method for evaluating CNNs. In Section 4, we present and discuss the results achieved in this work. Finally, Section 5 concludes the discussion and offers some final remarks.

2 RELATED WORK

Several efforts have been directed toward developing computational methods based on Artificial Intelligence (AI) to support breast cancer diagnosis, demonstrating the potential of deep learning with Convolutional Neural Networks (CNNs) to identify breast cancer in different stages using histopathological images (Gautam, 2023)(Springenberg et al., 2023).

(Zerouaoui and Idri, 2022) used a fusion of seven CNNs (DenseNet 201, Inception V3, Inception ResNet V2, MobileNet V2, ResNet 50, VGG16, and VGG19) as feature extractors and performed classification with four different classifiers (Decision Tree, Support Vector Machine, K-Nearest Neighbors, and Multilayer Perceptron).

(Abbasniya et al., 2022) employed IRv2-CXL method for binary classification of the BreakHis dataset. This method combines the Inception-ResNet-v2 architecture with an ensemble of CatBoost, XG-Boost, and LightGBM algorithms. However, the generalizability of the findings obtained with IRv2-CXL hasn't been evaluated in other datasets.

(Macedo et al., 2022) evaluated five CNNs trained on the BreakHis dataset to learn to distinguish between benign and malignant tumor nuclei. They subsequently tested these CNNs on a different dataset to classify and interpret tumor nuclei, quantifying the number of tumor nuclei cells in the segmented heat map generated by Grad-CAM after classification. However, they did not investigate the impact of parameters on classification and interpretation behaviors, limiting the depth of their analysis.

(Maleki et al., 2023) proposed an approach based on transfer learning for feature extraction from histopathological images in the BreakHis dataset. They used the extracted features as input for the extreme gradient boosting (XGBoost) classifier. The study evaluated different combinations of classifiers and pre-trained networks to enhance the classification performance.

(Majumdar et al., 2023) introduced a novel ensemble method based on rank fusion using the Gamma function. It combines the confidence scores of three transfer learning-based CNN models (GoogleNet, VGG11, and MobileNetV3). They specifically designed the ensemble model to classify breast histopathology images into two classes.

(Silva Neto, 2022) proposed a new dataset consisting of photomicrographs of the immunohistochemical expression of Biglycan (BGN) in breast tissue, including both cancerous and non-cancerous samples. Additionally, the study developed a CNN model inspired by LeNet-5 and evaluated its performance for classification. However, the author did not incorporate transfer learning and data augmentation techniques to address the limited number of images in the dataset.

Previous studies have focused on breast cancer classification using CNNs, but overlooked optimization and learning rate influence. To address this issue, we propose a novel approach that evaluates CNN performance, emphasizing interpretability, behavior, and key factors for hyperparameter optimization using partial factorial design.

3 PROPOSED APPROACH

We propose a comparative method to verify the influence of the optimizer and Learning Rate (LR) fac-

tors on the accuracy of different CNNs. Figure 1 illustrates the proposed method, which is divided into three (3) phases, as described as follows.

❶ **First Phase:** consists of training and validating six (6) different CNNs using the BreakHis (Spanhol et al., 2016) dataset, varying the optimizer parameters, and LR. The BreakHis breast cancer dataset consists of 7,909 microscopic images of breast tumor tissue from 82 patients, divided into benign (2,480 images) and malignant (5,429 images) tumors, with 700 $\times$ 460 pixels size. At the end of this phase, we verified which CNN performs better in the binary classification task.

❷ **Second Phase:** another dataset was considered, Biglycan (da Silva Neto et al., 2023), which is also from the context of breast cancer. The Biglycan breast cancer dataset consists of photomicrographs depicting the immunohistochemical expression of Biglycan (BGN) in breast tissue, both with and without cancer. The dataset comprises a total of 336 images with 128×128 pixels size and contains two (2) categories: malignant (203) and benign (133). In this phase, the goal is to verify which CNN performs better in the classification task using Biglycan dataset.

For both phases (❶ and ❷), we considered the variations of the optimizer parameters – Adam and Stochastic Gradient Descent (SGD) – and LR according to Table 1, leading to seventy-two (72) different training types of CNNs. Also, the datasets were randomly partitioned into 80% for training and 20% for testing. Finally, we resized all images to 224×224 pixels size and conducted the experiments using Python (version 3.8) and Pytorch 2.0 framework.

Table 1: Experiment Combinations for each CNN.

	AlexNet	EfficientNet	ResNet-50	ShuffleNet	SqueezeNet	VGG-16
Learning Rate	0.01	0.01	0.01	0.01	0.01	0.01
	0.001	0.001	0.001	0.001	0.001	0.001
	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Optimizer	SGD	SGD	SGD	SGD	SGD	SGD
	Adam	Adam	Adam	Adam	Adam	Adam
Dataset	BreakHis	BreakHis	BreakHis	BreakHis	BreakHis	BreakHis
	Biglycan	Biglycan	Biglycan	Biglycan	Biglycan	Biglycan

❸ **Third Phase:** consists of evaluating, using the partial factorial technique, based on the sum of squares, which factor impacts the most on the validation accuracy response variable. For this, we reduced the experimental space from 72 to eight different types of experiments. We selected the CNN with the best classification performance for each dataset and submitted it to a performance validation using the partial factorial design.

We based our reduced experimental design on a partial factorial with two factors and two levels labeled as (-1) and (1) according to Table 2. The first factor in our study is the Optimizer, followed by the LR. The Optimizer factor comprises two levels: Adam and SGD. The LR factor includes the following levels: 0.001 and 0.0001.

Table 2: Detailing of factors and levels with their Labels.

		Levels	
Factors	Optimizer - **A**	SGD (**-1**)	Adam (**1**)
	Learning Rate (LR) - **B**	0.001 (**-1**)	0.0001 (**1**)

Through the partial factorial method, we combined the factors and levels by providing an experimental combination according to Table 3. Thus, with a regression model, we carried out four experiments, using the combinations of each factor and level and measuring their influence on the Response Variable (y).

Table 3: Experiments Combinations.

Experiment	Learning Rate (LR)	Optimizer	Val. Accuracy
#1	**-1** (0.001)	**-1** (SGD)	y_1
#2	**1** (0.0001)	**-1** (SGD)	y_2
#3	**-1** (0.001)	**1** (Adam)	y_3
#4	**1** (0.0001)	**1** (Adam)	y_4

The goal of the third phase is to conduct a performance evaluation by doing four experiments for each dataset, following the combination in Table 3. Initially, we consider SGD as the level of the optimization function factor, which is an iterative method for optimizing an objective function with differentiable or sub-differentiable smoothness properties. It can be considered a stochastic approximation of gradient descent optimization, as it replaces the actual gradient with an estimate of it. Especially in high-dimensional optimization problems, this reduces the high computational cost, thus achieving faster iterations in exchange for a lower convergence rate. SGD is represented by Equation 1.

$$w_{t+1} = w_t - \eta_t \nabla E(w_t, b_t) \qquad (1)$$

Where w_t is the vector of parameters estimated in the t iteration, η_t is the learning rate, and $\nabla E(w_t, b_t)$ is the gradient of the objective function concerning the parameters. The goal of the performance evaluation in phase three (3) is to measure the percentage influence of the η_t (component of Equation 1) on the validation accuracy.

The other level of the optimization function factor that we experimented with in our performance eval-
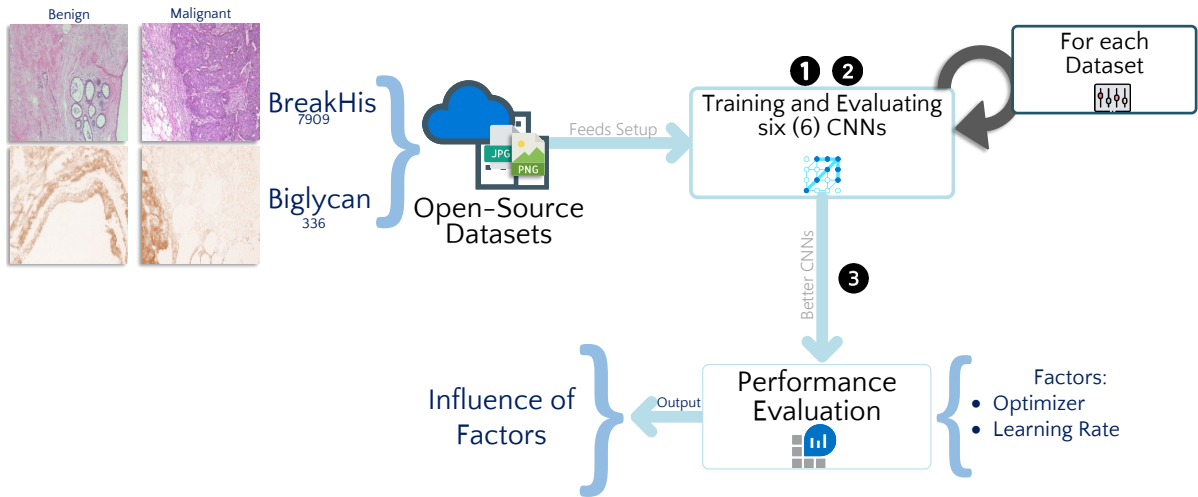
Figure 1: Proposed method.

uation is Adam, represented by Equation 2. Adam maintains an individual adaptive learning rate for each parameter of the model based on first-order moment estimates (gradient) and second-order moment estimates (moment). Additionally, it adjusts the learning rate adaptively for each parameter, allowing larger updates for common parameters and smaller updates for less common parameters.

$$\theta' = \theta - \alpha \frac{\hat{m}}{\sqrt{\hat{v}} + \varepsilon} \qquad (2)$$

Where θ is the updated parameter, θ' is the new parameter value, α is the interactive learning rate, $\hat{m}$ represents the first-order momentum, $\hat{v}$ represents the second-order momentum, and ε is the smoothing term. Therefore, with the performance evaluation design in phase three (3) of our method, it will be possible to verify the percentage influence of the α (a component of Equation 2) on the optimization function and, consequently, on the validation accuracy.

The Partial Factorial Method. To evaluate influence's level of each factor, we used the Sum of Squares. The regression model for the partial factorial design (2^2) is represented by Equation 3.

$$y = q_0 + q_A x_A + q_B x_B + q_{AB} x_{AB} \qquad (3)$$

The individual coefficients of each regression component can be obtained by breaking down Equation 3. The q_0 value, commonly referred to as the intercept term, signifies the baseline value of the dependent variable when all the other factors within the model are held at zero. By substituting the following four observations into the regression model, we can obtain the values of q_0, q_A, q_B, and q_{AB} according to the equations below: $q_0 = \frac{1}{4} \times (y_1 + y_2 + y_3 + y_4)$,

$q_A = \frac{1}{4} \times (-y_1 + y_2 - y_3 + y_4)$, $q_B = \frac{1}{4} \times (-y_1 - y_2 + y_3 + y_4)$, and $q_{AB} = \frac{1}{4} \times (y_1 - y_2 - y_3 + y_4)$.

Using the values of q_0, q_A, q_B, and q_{AB}, we can calculate the sum of squares, which represents the total variation in the response variable (y), as well as the variations attributed to the influence of factor A, factor B, and the interaction between A and B. The total variance of y, known as the Total Sum of Squares, is determined by Equation 4.

$$SST = 2^2 q_A^2 + 2^2 q_B^2 + 2^2 q_{AB}^2 \qquad (4)$$

The Sum of Squares due to the influence of A is $SS_A = 2^2 \cdot q_A^2$. The influence of A is given by $\frac{SS_A}{SST}$. Similarly, the Sum of Squares due to the influence of B is $SS_B = 2^2 \cdot q_B^2$, and the influence of Factor B as $\frac{SS_B}{SST}$. Lastly, we obtain the Sum of Squares due to the influence of Factors A and B together as $SS_{AB} = 2^2 \cdot q_{AB}^2$, and the influence of Factors A and B combined as $\frac{SS_{AB}}{SST}$.

4 RESULTS AND DISCUSSION

Initially, the six different CNNs: AlexNet (Krizhevsky et al., 2012), Efficient-Net (Tan and Le, 2020), ResNet-50 (He et al., 2016), ShuffleNet (Ma et al., 2018), SqueezeNet (Han et al., 2016), and VGG-16 (Simonyan and Zisserman, 2014)) were trained on each set of breast cancer images (BreakHis and Biglycan), considering training with data augmentation based on horizontal and vertical flips, and random rotation (-10° and 10°). Thus, according to Table 4, we recorded the best accuracy scores for each CNN, considering the combinations from Table 3. As indicated in

Table 4, EfficientNet CNN performed the best result on the BreakHis dataset, achieving an accuracy of 98.86%. Additionally, we report the best alpha (α) and the best optimizer, which in this case is Adam. Moving to the right side of Table 4, we find that the ShuffleNet performed the best on the Biglycan dataset, achieving an accuracy of 97.06% based on the validation accuracy.

Figure 2 presents loss and accuracy graphs to enrich our understanding of the generalization capacity of the better CNNs on the evaluated datasets. For the BreakHis, it is worth noting that CNN EfficientNet has a gradual learning process over epochs. Nonetheless, for the dataset Biglycan and ShuffleNet, it is suggestive that up until the 20th epoch, there is a progressive and suggestive learning pattern. However, in the subsequent epochs, the optimization function behaves inconsistently, resulting in irregular weights adjustment of the CNN throughout the epochs.

We selected the best CNN for each dataset based on the accuracies reported in Table 4. Therefore, we evaluated the influence of the optimizer and learning rate (LR) factors on the accuracies of these CNNs. The first set of experiments aimed to ensure that the CNNs were able to generalize on both datasets, BreakHis and Biglycan. The accuracy achieved on the BreakHis dataset is comparable to the state-of-the-art. However, Biglycan presented greater challenges for the CNNs due to its limited number of images. The second set of experiments involved combining different configurations and testing these combinations in a partial factorial design.

Table 5 presents the validation accuracies for different combinations of optimizers and learning rates (LR). For the BreakHis dataset, the CNN that achieved the highest performance (98.86%) was EfficientNet, using the Adam optimizer and LR of 0.001. Meanwhile, the best CNN for the Biglycan dataset was ShuffleNet, with an accuracy of 97.07% and using Adam optimizer and LR of 0.001. Tables 6 and 7 report the results of the second set of experiments in phase three (3) of our method.

Table 6 reports the percentage of influence of each factor (q_A, q_B, and q_{AB}) on the response variable, validation accuracy. The results obtained for the BreakHis dataset (Table 6) allow us to infer that the influence of Factor A, i.e., the optimizer alone, represents an impact of approximately 21.41% on the response variable, validation accuracy. On the other hand, Factor B (learning rate – LR) isolated represents an impact of approximately 23.60% on the response variable, validation accuracy. Lastly, we observed that the influence of Factors A and B (Optimization Function and Learning Rate) simultaneously

has a predominant impact of approximately 55.00% on the response variable, validation accuracy.

We sought to understand whether this behavior of the optimizer and learning rate factors' influence (q_A, q_B, and q_{AB}) carries over to other problems and datasets. Therefore, we carried out a performance evaluation using the Biglycan dataset and reported our findings in Table 7. We found that the influence of the optimizer and learning rate factors changes across problem classes and datasets. This perception is supported by the fact that the simultaneous influence of Factors A and B (Optimizer and LR) is negligible, accounting for approximately 1.79%. Meanwhile, Factor A (Optimizer) solely exerted a predominant influence of approximately 96.41% on the response variable, validation accuracy, for this dataset. On the other hand, Factor B (LR) alone had a negligible influence of approximately 1.79%.

Among the numerical findings suggested by our experiments, it is possible to recognize that formal analyses of factor influence using the partial factorial method can help guide optimization efforts toward factors that truely impact validation accuracy. Hyperparameter optimizers are recommended for fine-tuning CNNs, and the insights from our experiments can inspire new criteria for hyperparameter optimization, directing the tuning toward the search spaces of factors that have a predominant influence over others.

Finally, our best results achieved for each dataset were compared with other state-of-the-art approaches in the literature, as presented in Table 8. Our findings indicate that our best score exceeds the performance of the best state-of-the-art technique reported in previous studies.

5 CONCLUSION

This paper evaluated the extent to which two factors (optimization function and learning rate) influence the response variable and validation accuracy. To accomplish this, we proposed a three-fold method, where the initial two (2) phases involved training and validating six different CNNs using various parameter combinations and the two datasets, BreakHis and Biglycan. Subsequently, in the third phase, we selected two (2) CNNs that outperformed the others in the classification task and conducted a performance evaluation based on the sum of squares.

We found that the CNNs EfficientNet and ShuffleNet empirically outperformed the others in the classification task on the BreakHis and Biglycan datasets, achieving accuracies of 98.86% and 97.06%, both respectively. Additionally, our paper introduces an in-

Table 4: Overall CNNs Higher Performance.

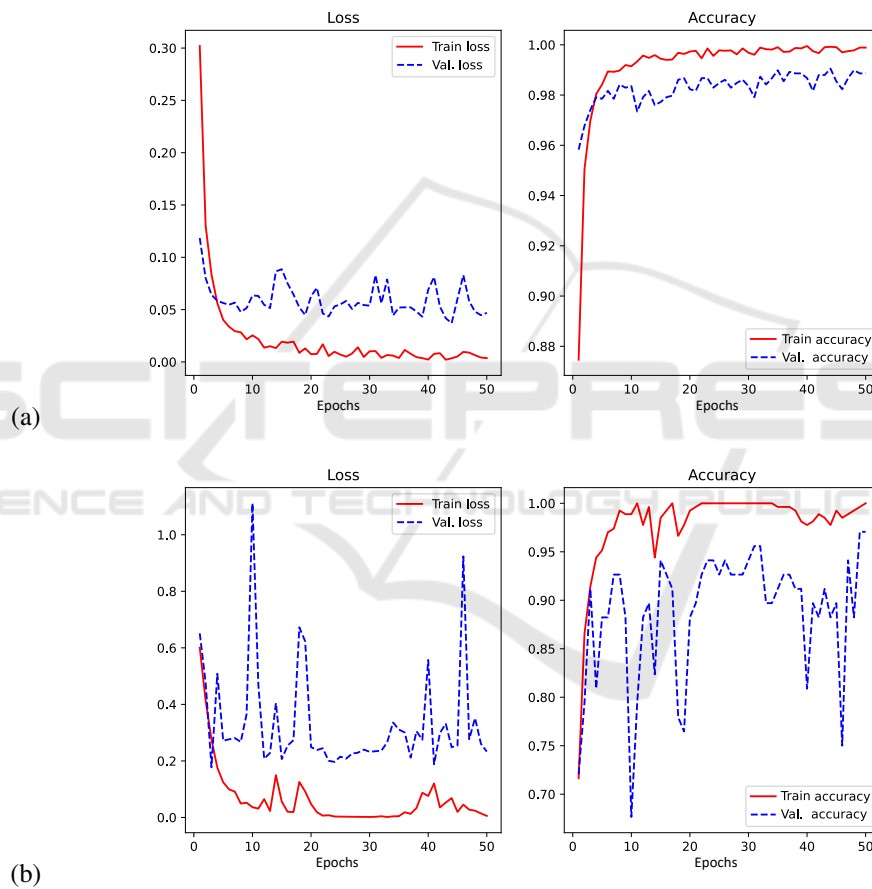|	Breakhis				Biglycan			
CNN	**alfa (α)**	**Acc. Train**	**Acc. Val.**	**Optimizer**	**alfa (α)**	**Acc. Train**	**Acc. Val.**	**Optimizer**
AlexNet	0.0001	99.87%	97.35%	SGD	0.0001	100%	91.18%	Adam
EfficientNet	**0.0001**	**99.89%**	**98.86%**	**Adam**	0.0001	100%	94.12%	Adam
ResNet-50	0.01	99.98%	98.80%	SGD	0.01	100%	95.59%	SGD
ShuffleNet	0.01	99.25%	98.29%	SGD	**0.001**	**100%**	**97.06%**	**Adam**
SqueezeNet	0.0001	95.84%	96.84%	Adam	0.0001	100%	94.12%	Adam
VGG-16	0.001	100%	98.55%	SGD	0.001	100%	95.59%	SGD

Figure 2: Generalization behavior through Loss and Accuracy Functions: (a) BreakHis; (b) Byglycan.

Table 5: Accuracies of the four (4) combinations of experiments for each dataset.

Factors			Response Variable: Val. Acc.	
Optimizer - A	**Learning Rate (LR) - B**	**AB**	**BreakHis**	**Biglycan**
SGD (-1)	0.001 (-1)	1	98.74%	60.29%
Adam (1)	0.001 (-1)	-1	92.48%	97.06%
SGD (-1)	0.0001 (1)	-1	97.41%	60.29%
Adam (1)	0.0001 (1)	1	98.86%	88.24%

Table 6: Breakhis: Estimation of The Influence of Factors, A, B, and AB Jointly.

Parameters	Estimated Variance	Variance (%)
	Val. Acc.	Val. Acc.
q_0	0.9687	
q_A (Optimizer)	-0.0120	21.41%
q_B (LR)	0.0126	23.60%
q_{AB} (Optimizer + LR)	0.0192	**55.00%**

Table 7: Biglycan: Estimation of The Influence of Factors, A, B, and AB Jointly.

Parameters	Estimated Variance	Variance (%)
	Val. Acc.	Val. Acc.
q_0	0,7647	
q_A (Optimizer)	0.1618	**96.41%**
q_B (LR)	-0.0220	1.79%
q_{AB} (Optimizer + LR)	-0.0225	1.79%

Table 8: Short Comparison with literature.

Dataset	Method	Accuracy (%)
BreakHis	(Zerouaoui and Idri, 2022)	92.56
	(Abbasniya et al., 2022)	96.46
	(Maleki et al., 2023)	91.9
	(Majumdar et al., 2023)	98.05
	Our approach	**98.86**
Biglycan	(Silva Neto, 2022)	93
	Our approach	**97.06**

novative approach by conducting a performance evaluation based on the sum of squares to estimate the influence of the optimizer and learning rate on validation accuracy. Using this method, we were able to determine that the combined influence of the optimizer and learning rate accounted for approximately 55.00% of the validation accuracy for the BreakHis dataset. Meanwhile, the optimizer factor alone had a predominant influence on validation accuracy, accounting for approximately 96.41% in the Biglycan dataset.

In addition to the reported quantitative results, our method provides insights and sheds light on a relevant issue in the context of optimization methods by indicating the percentage of the relevance of a variable in the optimization process and search within finite spaces. This empowers new efforts in exhaustive searches for variables that effectively impact the objective function.

In future work, we plan to evaluate the influence of other factors such as batch size and the internal

structure of the CNN, as well as assess patterns of influence across different datasets. In addition, we intend to expand the experiments by considering multiclass classification and expand the gathered insights and conclusions into more general and practically usable heuristics.

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