Noise in Datasets: What Are the Impacts on Classification Performance?

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Keywords: Machine Learning, Classifiers, Learning From Noisy Data, Class Noise, Attribute Noise.

Abstract: Classification is one of the fundamental tasks in machine learning. The quality of data is important in constructing any machine learning model with good prediction performance. Real-world data often suffer from noise which is usually referred to as errors, irregularities, and corruptions in a dataset. However, we have no control over the quality of data used in classification tasks. The presence of noise in a dataset poses three major negative consequences, viz. (i) a decrease in the classification accuracy (ii) an increase in the complexity of the induced classifier (iii) an increase in the training time. Therefore, it is important to systematically explore the effects of noise in classification performance. Even though there have been published studies on the effect of noise either for some particular learner or for some particular noise type, there is a lack of study where the impact of different noise on different learners has been investigated. In this work, we focus on both scenarios: various learners and various noise types and provide a detailed analysis of their effects on the prediction performance. We use five different classifiers (J48, Naive Bayes, Support Vector Machine, k-Nearest Neighbor, Random Forest) and 10 benchmark datasets from the UCI machine learning repository and three publicly available image datasets. Our results can be used to guide the development of noise handling mechanisms.

1 INTRODUCTION

In machine learning, classification is a supervised learning approach in which the model learns from the data given to it and makes new observations or predicts the class. The maximum prediction accuracy of a classifier depends on two factors (i) quality of the training data and (ii) the inductive bias of the algorithm(Zhu and Wu, 2004). But real-world datasets are not perfect and may suffer from noise. It is referred to as meaningless, erroneous, or corrupted data in a dataset.

In the data collection process, issues such as measurement errors, incomplete, corrupted, wrong, or distorted examples may be introduced (Libralon et al., 2009). This may result in errors in the values of the attributes or the class label(Nettleton et al., 2010). Noisy data may bias the learning process and make it difficult for the learner to build accurate models. Over the last few years, many algorithms have been developed to learn from noisy environments (Nazari et al., 2018). But the existence of noise can still introduce negative impacts. Therefore, it is important to develop some data preprocessing mechanisms that can effectively and efficiently deal with these types of data. In order to deal with real-world datasets, the algorithm requires an existing preprocessing module that will determine the impact of noise. Unfortunately, very few works have been conducted to investigate the impact of noise. This work investigates the impact of various noise types on different classifiers. Our aims are to extract information about the effect of different types and degrees of noise on these classifiers by systematically evaluating the effects of different types and degrees of noise in different learning paradigms. Our study investigates (i) is the performance of a classifier is hampered by noise? (ii) what is the impact of noise on the classifier if the training dataset is large enough? (iii) is there any robust classifier for noisy environments? (iv) class noise vs attribute noise: which one is more detrimental to the classification performance?

We aim at studying the performance of five classifiers including J48, Naive-Bayes (NB), Support Vector Machine (SVM), k Nearest Neighbor (k-NN), and Random Forest (RF). In our experiments, we employ linear classifiers as well as non-linear classifiers. Firstly, random class noise with different degrees is analyzed. Then we analyze the impact of attribute noise. Our work also aims to find a robust classifier

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Hasan, R. and Chu, C.
Noise in Datasets: What Are the Impacts on Classification Performance?.
DOI: 10.5220/0010782200003122
In *Proceedings of the 11th International Conference on Pattern Recognition Applications and Methods (ICPRAM 2022)*, pages 163-170
ISBN: 978-989-758-549-4; ISSN: 2184-4313

that is less sensitive to noise. One of the key attractions is that we take into account different characteristics of the dataset to provide a broader aspect of noise impacts. The results enable us to highlight the strong and weak classifiers in the presence of noise.

The rest of the paper is organized as follows. Section 2 discusses the related work. In Section 3, we differentiate between class and attribute noise as well as present our noise injection methodology. Section 4 reports the experimental results. Finally, we conclude the paper in Section 5.

2 RELATED WORK

Our work as described in Section 1 is motivated by the observation that while previous work have focused on the effect of class noise (Zhu and Wu, 2004), (Nazari et al., 2018), (Pelletier et al., 2017), (Algan and Ulusoy, 2020), there is limited attention to the impact of attribute noise in a dataset. The main limitation of some of these approaches is that they conducted experiments only for specific applications such as land cover mapping dataset (Nazari et al., 2018) or image dataset(Algan and Ulusoy, 2020). In the few studies that include different datasets, they consider only attribute noise (Nettleton et al., 2010), (da Costa et al., 2016), (Rolnick et al., 2017), (Saseendran et al., 2019). Little has been done to measure the impact of both types of noise such as attribute noise and class noise. Few works investigated the impact of both types of noises but for a specific learner (Zhu and Wu, 2004). The comparisons of the effect of noise on different learning paradigms have been neglected (Nazari et al., 2018), (Algan and Ulusoy, 2020), (da Costa et al., 2016), (Saseendran et al., 2019).

Few studies have reported the sensitivity of machine learning algorithms against noise. Most existing algorithms aim to learn directly from noisy data (Rolnick et al., 2017). Zhu and Wu (Zhu and Wu, 2004) showed that with an increase in the attribute noise, the accuracy of the classifier decreases linearly. They also demonstrated that eliminating instances containing class noise will likely enhance classification performance. However, their experiments were limited to a specific learner such as C4.5. Nettleton et al (Nettleton et al., 2010) also pointed out the impact of class noise and attribute noise. Their experimental results suggest that NB was more robust to noisy data and SVM was the weakest one. The drawback of their study is that they consider only binary classes. Even if the dataset contained multi-class, they transformed them into 2-class data sets. This could prevent the learners from truly uncovering the impact of noise.

We note that some other papers analyze how class noise can hamper the performance of some state-of-the-art classification models. Their results showed that classification performance is directly hampered in the presence of class noise (Zhu and Wu, 2004), (Nazari et al., 2018), (Pelletier et al., 2017), (Kalapanidas et al., 2003). Nevertheless their experiments did not include the impact of attribute noise. Moreover, they only focus on specific datasets such as image datasets, and land cover mapping datasets (Nazari et al., 2018), (da Costa et al., 2016).

3 METHODOLOGY

The quality of a dataset can be characterized by its attributes and class labels (Nazari et al., 2018). This section discusses two categories of noise and a brief discussion about the classifiers we used in our experiments.

3.1 Class Noise

Class noise is known as labeling errors when an instance is incorrectly labeled. There are several causes for class noise such as subjectivity during the labeling process, data entry errors, or inadequacy of the information used to label each example. There are two types of class noise:

- Contradictory examples: Some examples appear more than once with different class labels.
- Misclassifications: Some examples are labeled incorrectly.

3.2 Attribute Noise

Attribute noise refers to corruption in the value of one or more attributes. There are three types of attribute noise:

- Erroneous attribute: The attribute with a wrong value
- Missing attribute values: The value of an attribute is unknown. Generally, it is represented as a "?" sign.
- Don't care values: The value of the attribute does not affect the rest of the values in the example

3.3 Noise Injection

In the following we describe how we introduce noise in class labels and attributes. It is difficult to have real-datasets where attribute and class noise are clearly

Table 1: UCI Dataset Characteristics.

Dataset	Instances	Attributes	Class	Missing values	Dataset characteristics	Attribute characteristics	Balanced?
Credit card	690	15	2	37	Multivariate	Categorical, Integer, Real	No
Iris	150	4	3	None	Multivariate	Real	Yes
Spect	267	22	2	None	Multivariate	Categorical	No
Glass	214	10	7	None	Multivariate	Real	No
Wdbc	569	32	2	None	Multivariate	Real	No
Wine	178	13	3	None	Multivariate	Integer,Real	No
Dermatology	366	33	6	8	Multivariate	Categorical, Integer	No
Ecoli	336	8	8	None	Multivariate	Real	No
Segmentation	2310	19	7	None	Multivariate	Real	Yes
Yeast	1484	8	10	None	Multivariate	Real	No

identified (Pelletier et al., 2017). To overcome such limitations, we inject artificial noise into our datasets.

3.3.1 Attribute Noise Injection

We generate the attribute noise in the training data set using Gaussian noise. Therefore, the values that the noise can take on are Gaussian distributed. The probability density function of a Gaussian random variable ζ is given by

$$p(\zeta) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(\zeta-\mu)^2 / 2\sigma^2} \tag{1}$$

where μ is the mean of the distribution and σ is the standard deviation.

3.3.2 Class Noise Injection

We followed the random noise model for class noise injection. The percentage of noisy levels varies from 10% to 50%, with an interval of 10%. The class label is changed from its current value to one of the other possibly one, randomly. For instance, if there are 300 examples in a dataset, then adding a noise level of 10% implies that 30 labels will change randomly.

3.4 Choice of Classifiers

In the literature, there is a lack of work to analyze the impact of noise on different types of classifiers. Therefore, we select five classifiers for our experiments. We divide our selected classifiers into two categories (i) Linear classifiers: NB and SVM, and (ii) Non-linear classifiers: J48, RF, and *k*-NN.

The rationale for choosing the classifiers based on their characteristics are three-fold: (i) Firstly, J48, *k*-NN, and RF are non-linear classifiers that are useful for problems that are linearly non-separable; i.e., the class boundaries cannot be approximated well with a planar surface. These boundaries can suffer from overfitting. While there are methods such as pruning in decision trees designed to reduce the chance that the trees are overfitting (Quinlan, 2014), a natural question is how sensitive they are to noise in data. Secondly, NB is a linear model for classification which leads to a linear decision boundary that has been found effective in many problem domains. Thirdly, each classifier has its own inherent noise handling mechanism. It allows us a better understanding of the results of the impact of noise on them. For example, the NB algorithm assumes each attribute is independent of each other. This could provide an added advantage when noise is introduced to the dataset. SVM when used to find a linear boundary in the feature space (such as by using a polynomial kernel with degree 1) can be considered to optimize the boundary to be equally distant from the closest points of either class. A comparison of NB with the linear SVM can reveal whether the optimized boundary of the SVM improves the handling of noise.

4 EXPERIMENTS AND RESULTS

A study on either class noise or attribute noise alone cannot provide enough information about classifier behaviors against noise. Accordingly, a study of different types of noise on different learners is required to achieve a meaningful conclusion while evaluating classifier behavior in noisy environments. Keeping this in mind, we conduct our experiments (i) in presence of class noise and attribute noise (ii) use different classifiers (iii) large training datasets (iv) different characteristics of datasets. Our results provide an insightful view of classification performance in noisy environments. In the following, we describe the main aspects of the experimental results of this study.

4.1 Datasets

The experiments carried out in this paper are based on 13 datasets of which 10 datasets are collected from the UCI machine learning repository (Dua and Graff, 2017) and 3 publicly available image datasets. Table 1 summarizes the dataset characteristics from UCI and Table 2 presents the details of the image datasets.

The reason for choosing different datasets is to investigate if the classification performance is hampered by the characteristics of the dataset. For instance, missing values in a dataset are a common form of attribute noise. Therefore, we deliberately choose some datasets with missing values. It would be worth experimenting to see how classifiers behave in such a scenario. In addition, we focus on imbalanced data sets. In such data sets, the distribution can vary from a slight bias to a severe imbalance where there could be one example in the minority class for hundreds, thousands, or millions of examples in the majority of the class or classes. For instance, the class distribution of the wdbc data set is 62.74% for the positive class and 37.26% for the negative class. In imbalanced data, the minority class is more sensitive than the majority class. Therefore, we include both balanced and imbalanced datasets in our experiments. Fig. 1 illustrates the class distribution for each UCI dataset included in our experiments.

We also include large training datasets such as CIFAR-10, MNIST, and Fashion-MNIST. As an example, the training data for CIFAR-10 is 60,000.

Table 2: Characteristics of Image Datasets.

Dataset	Training set	Testing set	class	Balanced?
MNIST	60000	10000	10	No
Fashion-MNIST	60000	10000	10	Yes
CIFAR-10	50000	10000	10	Yes

4.2 Experimental Setup

In our experimental setup, we divide the UCI datasets into three categories:

- Balanced dataset: Each class has equal distribution (iris, and segmentation dataset)
- Slightly balanced dataset: The distribution of classes is uneven by a small amount. In our setting, if the majority class to minority class ratio is between 1:1 to 1:69, we define it as a slightly imbalanced dataset (credit card, spect, glass, wdbc, wine, and dermatology dataset)
- Highly imbalanced dataset: The distribution of classes is uneven by a large amount. In our setting, if the majority class to minority class ratio is greater than 1:70, we define it as a highly imbalanced dataset (ecoli, and yeast dataset)

To evaluate the performance of noise on classification performance, we use 2 different evaluation metrics :

- AUROC: The AUROC computes the area under the ROC curve. The ROC curve plots the true positive rate vs false positive rate at various threshold settings. In our experiments, we use AUROC for balanced and slightly imbalanced datasets. This is because the AUROC gives the same result regardless of what the class probabilities are.
- AUPRC: AUPRC is defined as the average of precision scores calculated for each recall threshold. We use AUPRC for highly imbalanced datasets as it focuses mainly on the positive class.

In the case of image datasets, we use the loss function to evaluate the performance of the deep neural network. The loss function we use in our experiments is categorical cross-entropy.

We split our dataset into training and test sets. To preserve the percentage of samples for each class, we use a variation of K-fold named stratified K-fold. The value for K is set to 10 because the low values of K will result in a noisy estimate of model performance and a very large value will result in a less noisy estimate of model performance.

When simulating class noise, the training dataset is corrupted with varying degrees of noise while keeping the test dataset clean. It allows us to evaluate the true performance of the classifier. In the case of class noise, random noises are injected with rates of 10%, 20%, 30%, 40%, and 50%. We restrict our noise level up to 50% of the original dataset because in realistic situations only certain types of classes are likely to be mislabeled. For attribute noise, we use Gaussian noise with zero mean and 2 different variance values of 0.5 and 0.7. In image datasets, we vary the value of variance from 0.1 to 0.9. The reason is that with a small variance a noisy image can still have good performance and the distortion level will be minimum. Hence, we want to observe the performance with different variances of noise. For image datasets, we corrupted the training data with Gaussian noise and evaluated it with test data.

For class noise evaluation, we use the Weka tool (Eibe et al., 2016). It is a free software tool for data mining tasks. In the case of attribute noise evaluation, we implemented the noise injection model and the classifiers in Python 3.5. The parameter settings for five classifiers are as follows: J48 (confidence factor C=0.25), NB (bacthSzie=100, useKernelEstimator=False), SVM (kernel: polynomial kernel with degree 1, tolerance parameter=0.001), k-NN (k=1, distance: euclidean distance) and RF (bagSizePercent=100, maxDepth=0, numIterations=100). All the experiments were run on Mac OS Big Sur with a 3.1 GHz CPU and 8GB memory.

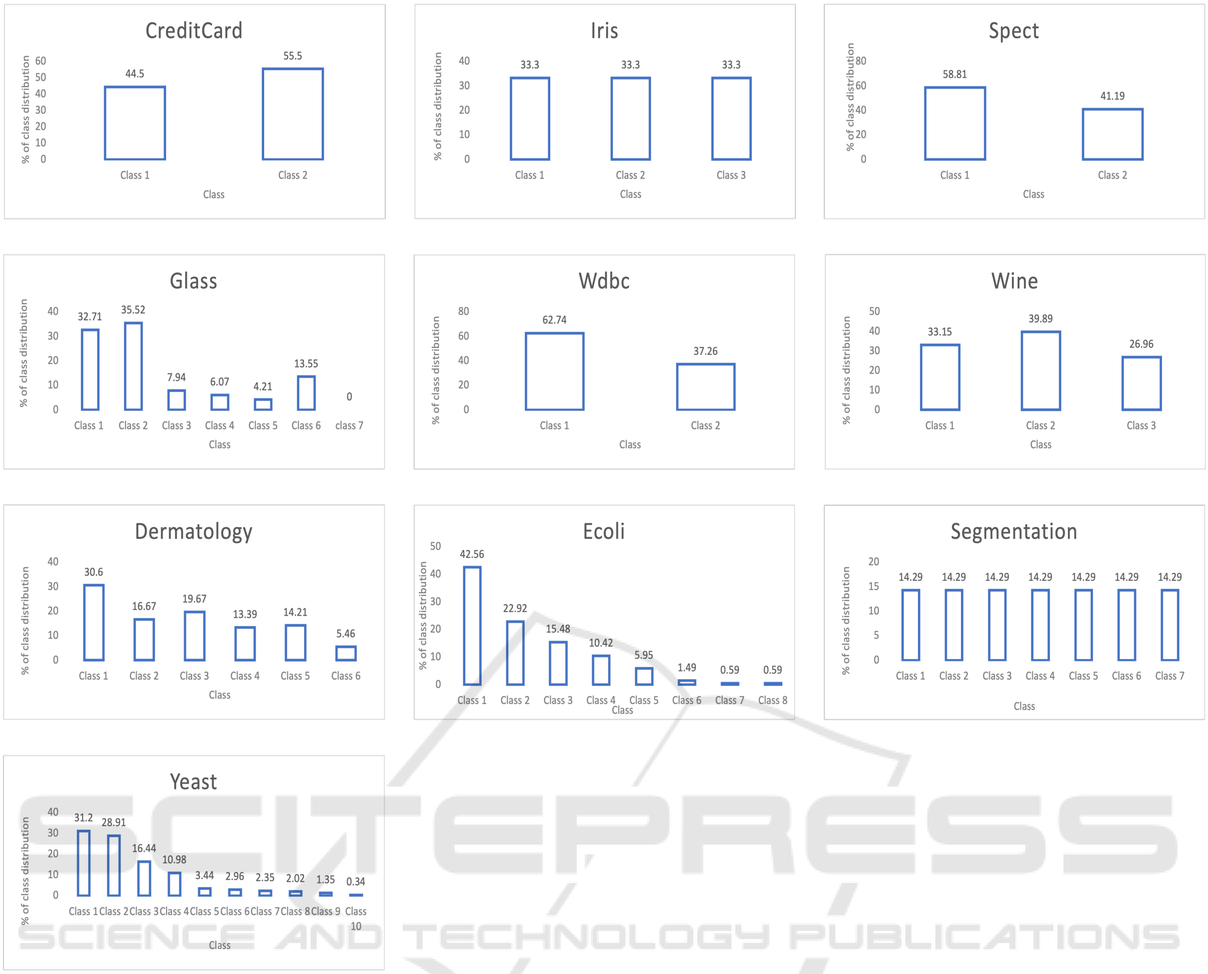


Figure 1: Class Distribution of UCI Datasets.

Table 3: Rank of Classifiers.

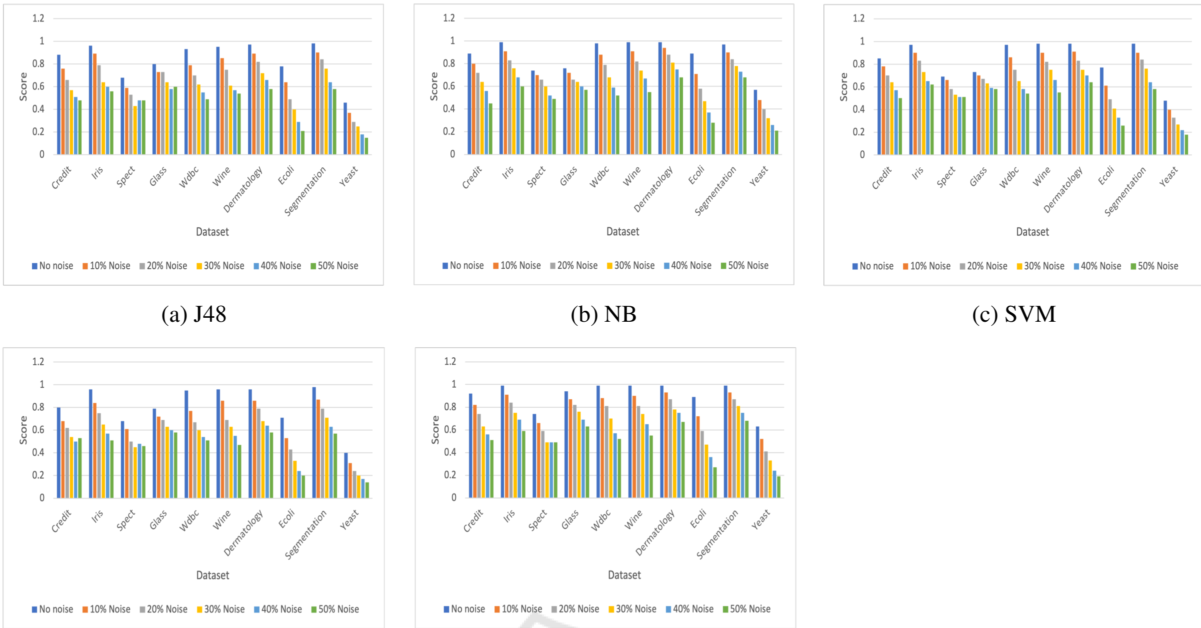
Classifiers	10% Noise	20% Noise	30% Noise	40% Noise	50% Noise	Avg Score	Rank
J48	0.74	0.66	0.56	0.50	0.46	0.58	4
NB	0.79	0.71	0.64	0.57	0.50	0.64	2
SVM	0.76	0.68	0.61	0.54	0.49	0.61	3
K-NN	0.70	0.61	0.54	0.49	0.45	0.56	5
RF	0.81	0.73	0.64	0.57	0.51	0.65	1

4.3 Results

We evaluated our experimental results in presence of attribute noise and class noise. For each type of noise, we use the same five classifiers. The following subsection presents the results of various experiments.

4.3.1 Effects of Class Noise

In our first analysis, we compare the performance of different classifiers in the presence of varying degrees of class noise. We use the same classifiers for each of the settings. The datasets used in this setting are from the UCI repository. They have been testified to be appropriate in many algorithms in the literature(Libralon et al., 2009). The typical assumption is that these datasets are clean and noise-free(Libralon et al., 2009). But there are missing values in these datasets. In our experiments, we replace all missing values for nominal and numeric attributes in a dataset with the modes and means from the training data. Firstly, we train and test each dataset using our selected five classifiers. Then we gradually increase the noise level to test how these classifiers behave.



(a) J48 (b) NB (c) SVM

(d) K-NN (e) RF

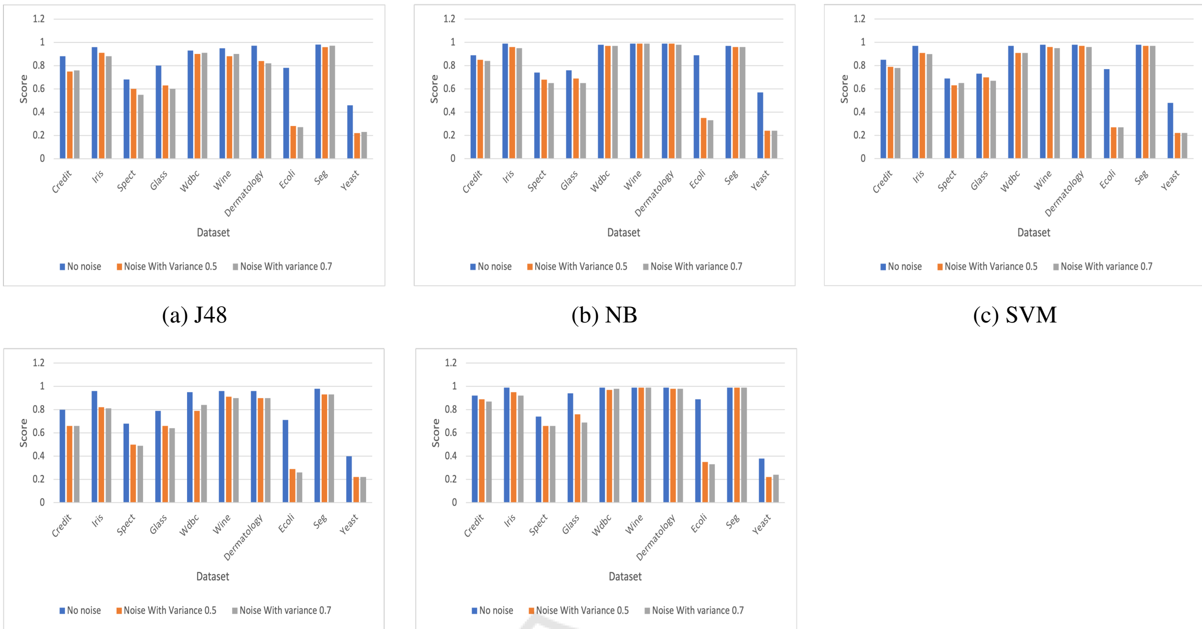
Figure 2: Effects of class noise on different classifiers. The y axis represents the AUROC score except for Ecoli and Yeast. AUPRC score is reported for Ecoli and Yeast dataset. Six color bar represents the prediction accuracy when six different noise labels are applied for each dataset.

Fig. 2 shows the classification results obtained by J48, NB, SVM, *k*-NN, and RF. As can be seen from the figures, the classification performance drops significantly with an increase in noise. We observed that this statement is true for all classifiers in spite of the classifiers' inherent noise handling mechanisms. One key observation is that: when analyzing the situation with high levels of noise, the classifiers fail to learn from the data and make the classification task difficult. For example, when the degree of noise is 50%, we see a significant drop in the prediction performance. The score is below 60% for almost all of the datasets. However, this is expected behavior since it is harder to classify the data due to high levels of noise. However, from Fig. 2, it is also clear that even in the presence of a little noise, the performance of each classifier is hampered.

We also computed the average rank of each classifier. Firstly, we computed the average score of each classifier. For instance, the average score of J48 classifier in different noise levels are 0.74(10% noise), 0.66(20% noise), 0.56(30% noise), 0.50(40% noise) and 0.46(50% noise). We rank the learners according to the prediction score. The highest value of prediction score ranks first. With a reference to Table 3, RF ranks first while the last rank belongs to *k*-NN. It is important to notice that in the case of low noise(10%), the rank remains the same but with a high level of noise(50%) NB performs very well compared to the other classifiers except RF. However, *k*-NN always demonstrates the worst performance in every setting. Another important observation is that the performance of linear classifiers (average score is 0.63) is better than non-linear classifiers (average score is 0.60)

4.3.2 Effects of Attribute Noise

To evaluate the impact of attribute noise, we use the same datasets used for class noise evaluation. The prediction score obtained without noise and with noise are illustrated in Fig. 3. In presence of attribute noise, on 7 out of 10 datasets, the prediction performance degrades for each classifier. The exception is for wine, dermatology, and segmentation dataset when we use NB and RF classifier model. It is important to note that the performance degrades very little when we increase the variance from 0.5 to 0.7. We also presented a ranking of classifiers in Table 4. We followed the similar ranking procedure described in the previous paragraph. The highest prediction score comes from the classifier RF and the lowest from *k*-NN. We also observe that the performance of linear classifiers (average score is 0.74) is better than non-linear classifiers (average score is 0.70).



(a) J48 (b) NB (c) SVM

(d) K-NN (e) RF

Figure 3: Effects of attribute noise on different classifiers. The y axis represents the AUROC score except for Ecoli and Yeast. AUPRC score is reported for Ecoli and Yeast dataset.

Table 4: Rank of Classifiers.

Classifiers	Noise(σ^2=0.5)	Noise(σ^2=0.7)	Avg	Rank
J48	0.69	0.68	0.69	4
NB	0.76	0.75	0.76	2
SVM	0.73	0.72	0.73	3
K-NN	0.66	0.66	0.66	5
RF	0.77	0.76	0.77	1

4.3.3 Effects of Noise in Deep Learning

We conduct another set of experiments to evaluate the impacts of noise on deep neural networks for multi-classification tasks. Deep neural networks are capable of generalizing from training data(Nazaré et al., 2017). So, our goal of this experiment is: can deep neural networks still be able to generalize after training on noisy data? Fig. 4 demonstrates the results obtained from three image datasets: MNIST, Fashion-MNIST, and CIFAR-10. We inject Gaussian noise in each of the datasets with a variance ranging from 0.1 to 0.9. We use Convolution Neural Network (CNN) with the following parameter settings: (i) model: sequential (ii) activation function: relu, and softmax (iii) loss function: categorical cross-entropy and (iv)optimizer:adam. From Fig. 4, we can see that the performance drops in case of low variance as well as high variance. Therefore, we can conclude that deep neural networks fail to generalize in presence of noise.

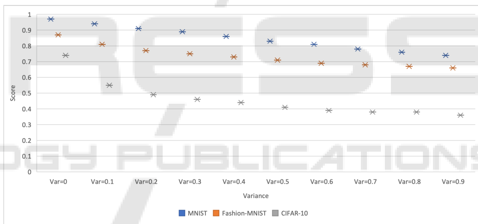


Figure 4: Effect of noise on MNIST, Fashion-MNIST and CIFAR-10 dataset.

4.3.4 Key Takeaways from Our Results

We observe some interesting facts from our results. The key observations from our experiments are

- Class noise degrades the classification performance
- The attribute noise is also harmful and could bring severe problems to classifiers
- Class noise is more dangerous than attribute noise
- Random forest is more resilient to noise and *k*-NN is the weakest one
- Linear classifiers are more tolerant to noise than non-linear classifiers
- Deep neural network finds difficulty to generalize after training on massively noisy data

5 CONCLUSIONS

This paper investigated the impacts of noise on various classifiers in various environment settings. We analyzed how attribute noise and class noise affect the quality of the models. The five well-known classifiers including J48, NB, SVM, *k*-NN, SVM, and RF have been compared with different noise levels. The general results show that both types of noise have adverse effects on each classifier. The simple observation is that RF is the best learner and *k*-NN gives the worst performance in a noisy environment. Another observation is that deep neural networks are not robust to noise. Our experimental results may serve either as a guideline for the selection of appropriate classifiers in noisy environments or for developing noise handling mechanisms.

ACKNOWLEDGMENTS

This work is supported by the U.S. National Science Foundation under grant number OIA-1946231 and the Louisiana Board of Regents for the Louisiana Materials Design Alliance (LAMDA).

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