m-arcsinh: An Efficient and Reliable Function for SVM and MLP in scikit-learn

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Abstract

This paper describes the ‘m-arcsinh’, a modified (‘m-’) version of the inverse hyperbolic sine function (‘arcsinh’). Kernel and activation functions enable Machine Learning (ML)-based algorithms, such as Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP), to learn from data in a supervised manner. m-arcsinh, implemented in the open source Python library ‘scikit-learn’, is hereby presented as an efficient and reliable kernel and activation function for SVM and MLP respectively. Improvements in reliability and speed to convergence in classification tasks on fifteen (N = 15) datasets available from scikit-learn and the University California Irvine (UCI) Machine Learning repository are discussed. Experimental results demonstrate the overall competitive classification performance of both SVM and MLP, achieved via the proposed function. This function is compared to gold standard kernel and activation functions, demonstrating its overall competitive reliability regardless of the complexity of the classification tasks involved.

Keywords: Kernel, Activation, Support Vector Machine, Multi-Layer Perceptron, Scikit-learn

1. Introduction

Despite theoretical advances in both kernel and activation functions respectively for optimal separating hyperplane (OSH)-based classifiers, such as the Support Vector Machine (SVM) (Cortes and Vapnik, 1995), and Artificial Neural Networks (ANN), e.g., the Multi-Layer Perceptron (MLP) (Rumelhart et al., 1986), usable, reproducible and replicable functions for both the SVM and the MLP have remained limited and confined to two limited sets of functions deemed as ‘gold standard’. Both sets of functions have been made freely accessible in the open source Python library named ‘scikit-learn’ (Pedregosa et al., 2011) for Machine Learning, under the related ‘MLPClassifier’ and the ‘SVC’ (Support Vector Classifier) classes, which respectively implement the MLP and SVM for classification. The availability of these functions to the public has made it possible for ecosystems of organisations across academia and industry to leverage these assets for various purposes and applications, ranging from teaching aids to practical user-centred implementations (Buitinck et al., 2013).
Nevertheless, both sets of functions are not only limited with respect to their number, but also they may not always lead to reliable outcomes when applied for classification, e.g., causing slow or lack of convergence (Vert and Vert, 2006) (Jacot et al., 2018), due to trapping at local minima (Parisi et al., 2020). Moreover, both sets of functions are mutually exclusive (Pedregosa et al., 2011), given the challenge in deriving a mathematical function that can be used as a kernel function for SVM and as an activation function for MLP concurrently. The only similarity between them is the presence of the 'sigmoid' kernel function in SVM and its modified version named 'tanh' or 'hyperbolic tangent sigmoid' (Lin and Lin, 2003), which has an extended range \([-1, +1]\), as opposed to \([0, +1]\) and a stronger gradient due to steeper derivatives, making it more suitable for ANN, such as the MLP, rather than OSH-based classifiers, e.g., SVM.

Therefore, there is an increasing need for additional open source kernel and activation functions, which reach convergence faster, avoiding trapping at local minima, are more stable and can also be used across multiple algorithms. Entirely written in Python and made freely available in 'scikit-learn' (Pedregosa et al., 2011) for both the 'MLPClassifier' and the 'SVC' classes, the proposed hyperbolic function is demonstrated as a competitive function with respect to gold standard functions, which suits both kernel and activation functions' requirements, thus being computationally efficient and reliable.

Thanks to its liberal license, it has been widely distributed as a part of the free software Python library 'scikit-learn' (Pedregosa et al., 2011), and it is available for use for both academic research and commercial purposes.

2. Methods

2.1 Datasets used from scikit-learn and the UCI ML repository

The following datasets from scikit-learn were used in the experiments described and discussed in this study:

- 'Breast cancer Wisconsin (diagnostic)' dataset (Wolberg et al., 1995), having 30 characteristics of cell nuclei from 569 digitised images of a fine needle aspirate of breast masses, to detect whether they correspond to either malignant or benign breast cancer;

- 'LFW people' dataset (Huang et al., 2007) (Learned-Miller, 2014), which has 13,233 JPEG photos of 5,749 famous people collected from the Internet, each of which is composed of 5,828 features, to identify the individual appearing on each photo;

- 'Iris' dataset (Anderson, 1936) (Fisher, 1936), which has three species of one-hundred and fifty (N=150) 'Iris' flowers to be classified based on four features describing their petals and sepals;

- 'Handwritten Digits' dataset (Alpaydin and Kaynak, 1998), to recognise handwritten digits (from 0 to 9), given about 180 images per class (1,797 images in total) and 64 features per each image;
• 'Wine' dataset (Forina et al., 1991), which has 13 features derived from 178 measurements obtained via a chemical analysis of wines grown in the same region in Italy by three different cultivators, to understand whether such measurements and different constituents correspond to one of three types of wine (59 measurements for the first type, 71 for the second type, 48 for the third type);

• 'Olivetti faces' dataset (Roweis, 2017) with (only) 10 different 64x64 images of the faces of 40 different subjects - to be identified via classification - taken between April 1992 and April 1994 at the 'AT and T' Laboratories Cambridge. Such photos were taken against a dark homogeneous background at different times, with various lighting, facial expressions (open/closed eyes, smiling/not smiling) and details (glasses/no glasses). Subjects were in an upright, frontal position, with little side movement at time;

Moreover, the following datasets from *The University California Irvine (UCI) ML repository* were used for additional evaluation in this study:

• 'Optical Recognition of Handwritten Digits' (OptDigits) datasets (Kaynak, 1995), to recognise handwritten digits (from 0 to 9), given 5,620 images in total and 64 features per each image, from 43 people, 30 of which contributed to the training data partition and the remaining 13 to the partition for testing:

  – training data partition ('optdigits.tra' file);
  – testing data partition ('optdigits.tes' file);

• Heart failure clinical records dataset (Chicco and Jurman, 2020), to predict whether a patient was deceased during the follow-up period, based on 13 clinical features from medical records of 299 patients who had heart failure;

• Parkinsons dataset (Little et al., 2007), which has 23 features corresponding to 195 biomedical voice measurements from 31 people, 23 with Parkinson's disease (PD), to help in detecting PD from speech signals;

• Haberman survival dataset (Lim, 1999), with three features (age of patient at time of operation; patient's year of operation; number of positive axillary nodes detected) to predict whether 306 patients who had undergone surgery for breast cancer would have died within 5 years of follow up or survived for longer;

• SPECTF dataset (Cios et al., 2001), which has 267 images collected via a cardiac Single Proton Emission Computed Tomography (SPECT), describing whether each patient has a physiological or pathophysiological heart based on 44 features:

  – training data partition ('SPECTF.train' file), with 80 images;
  – testing data partition ('SPECTF.test' file), which has 187 images;

• German Statlog credit data (Hofmann, 1994), to identify whether a customer is associated with a good or bad credit risk based on 20 features;
• Pen-based handwritten digits recognition dataset (Alpaydin in and Alimoglu, 1998), to recognize handwritten digits (from 0 to 9), drawn on a WACOM PL-100V pressure sensitive tablet with an integrated LCD display and a cordless stylus, based on 250 images from 44 writers:
  
  – training data partition (’pendigits.tra’ file), with images from 30 writers;
  – testing data partition (’pendigits.tes’ file), which has images from the remaining 14 writers;

• Wireless Indoor Localization dataset (Bhatt, 2005) (Rohra et al., 2017), which has 7 features characterising the strength of a Wi-Fi signal observed on a smartphone in indoor spaces to identify if an individual was in one of four rooms;

• ’Breast Cancer Coimbra dataset (Patrício et al., 2018), with 10 clinical features, including anthropometric data and parameters collected via haematological analysis, measured for 64 patients with breast cancer and 52 healthy controls to identify the presence or absence of breast cancer.

2.2 Baseline SVM and MLP models and hyperparameters

As the purpose of this study is not to devise the most optimised, best-performing classifier for any of the classification tasks involved in 2.1, but, instead, to develop a novel computationally efficient and reliable kernel and activation function and evaluate it against the two sets of gold standard functions available in the Python library ‘scikit-learn’ (Pedregosa et al., 2011) under the ‘MLPClassifier’ and the ‘SVC’ classes, baseline SVM and MLP models were used with the following hyperparameters for all classification tasks in 2.1:

• MLP-related hyperparameters:
  
  – ’random_state’ = 1;
  – ’max_iter’ = 300, where ’max_iter’ is the maximum number of iterations.

Listing 1 provides the snippet of code in Python to use an MLP with different activation functions available in ‘scikit-learn’ (Pedregosa et al., 2011), including the novel ’m-arcsinh’.

Listing 1: MLP with different activation functions available in ‘scikit-learn’ (Pedregosa et al., 2011), including the proposed ’m-arcsinh’.

```python
from sklearn.neural_network import MLPClassifier

for activation in ('identity', 'logistic', 'tanh', 'relu', 'm-arcsinh'):
    classifier = MLPClassifier(activation=activation, random_state=1, max_iter=300)
```
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- SVM-related hyperparameters:
  - ‘gamma’ = 0.001, where ‘gamma’ is the kernel coefficient for the rbf, poly and sigmoid kernel functions;
  - ‘random_state’ = 13;
  - ‘class_weight’ = ‘balanced’, setting the parameter C by adjusting the weights to be inversely proportional to the class frequencies in the input data.

Listing 2 provides the snippet of code in Python to use an SVM with different kernel functions available in ‘scikit-learn’ (Pedregosa et al., 2011), including the novel ‘m-arcsinh’.

Listing 2: SVM with different kernel functions available in ‘scikit-learn’ (Pedregosa et al., 2011), including the proposed ‘m-arcsinh’.

```python
from sklearn import svm

for kernel in ('linear', 'poly', 'rbf', 'sigmoid', 'm_arcsinh '):
    classifier = svm.SVC(kernel=kernel, gamma=0.001, random_state=13,
                         class_weight='balanced ')
```

Where the data were not already provided in two separate partitions for training and testing (see 2.1), the datasets were split via ‘train_test_split’ in ‘scikit-learn’ (Pedregosa et al., 2011) from ‘sklearn.model_selection’ as follows, without randomisation (‘shuffle’=False):

- 70% of the data was selected for training, whilst the remaining 30% for testing for the 'Handwritten Digits' dataset;
- 80% for training, 20% for testing for the 'Statlog', 'Olivetti faces', 'Parkinson’s', 'Wi-Fi localization', 'Breast Cancer Coimbra', 'Haberman' and 'Heart Failure' datasets;
- 75% for training, 25% for testing for the 'LFW people' dataset.

2.3 m-arcsinh: A new kernel and activation function

For a function to be both generalised as a kernel and activation function for SVM and MLP, it has to be able to 1) maximise the margin width in SVM and 2) improve discrimination of input data into target classes via a transfer mechanism of appropriately extended range for MLP. Two functions that satisfy the two above-mentioned requirements are the linear kernel for SVM and tanh for MLP. Nevertheless, whilst the linear kernel is not suitable in MLP to leverage gradient descent training appropriately in presence of non-linearly separable data, the tanh function has an extended range with sigmoidal behaviour for SVM to maximise the margin width reliably with such data.

Thus, a novel function was devised to be suitable for both SVM and MLP concurrently by leveraging a weighted interaction effect between the hyperbolic nature of the inverse
The hyperbolic sine function (‘arcsinh’), suitable for MLP, and the slightly non-linear characteristic of the squared root function, appropriate for SVM. With higher weight (1/3) given to the ‘arcsinh’ and a slightly lower one (1/4) to the square root function, hence satisfying both the above-mentioned requirements 1) and 2) concurrently, the following modified (m-) arcsinh (m-arcsinh) was derived:

$$arcsinh(x) \times \frac{1}{3} \times \frac{1}{4} \times \sqrt{|x|} = arcsinh(x) \times \frac{1}{12} \times \sqrt{|x|}$$

(1)

The derivative of m-arcsinh can be expressed as:

$$\sqrt{|x|} \times \frac{1}{24 \times |x|^{3/2}} + \frac{x \cdot arcsinh(x)}{24 \times |x|^{3/2}}$$

The graphs illustrate the function's behavior over the range of x values from -10 to 10.
Listing 3 provides the snippet of code in Python that implements the proposed m-arcsinh function as a kernel for an SVM classifier or 'SVC' in 'scikit-learn' (Pedregosa et al., 2011).

Listing 3: Using the m-arcsinh function as a kernel for an SVM classifier or 'SVC' in 'scikit-learn' (Pedregosa et al., 2011).

```python
import numpy as np
from sklearn import svm

# X is the numpy ndarray of the inputs to classify,
# Y is the numpy ndarray of the target classes.
def m_arcsinh(X, Y):
    return np.dot((1/3*np.arcsinh(X))*(1/4*np.sqrt(np.abs(X))),(1/3*np.arcsinh(Y.T))*(1/4*np.sqrt(np.abs(Y.T))))

classifier = svm.SVC(kernel=m_arcsinh, gamma=0.001, random_state=13, class_weight='balanced')
```

Listing 4 provides the snippet of code in Python that implements the proposed m-arcsinh function (1) as an activation and its derivative (2) for an MLP classifier or 'MLPClassifier' in 'scikit-learn' (Pedregosa et al., 2011).

Listing 4: Using the m-arcsinh function as a kernel for an MLP classifier or 'MLPClassifier' in 'scikit-learn' (Pedregosa et al., 2011).

```python
import numpy as np
from sklearn.neural_network import MLPClassifier

def m_arcsinh(X):
    """Compute the m-arcsinh hyperbolic function in place."

    Parameters
    ----------
    X: {array-like, sparse matrix}, shape (n_samples, n_features)
       The input data.

    Returns
    -------
    X_new: {array-like, sparse matrix}, shape (n_samples, n_features)
       The transformed data.
    """
    return (1/3*np.arcsinh(X))*(1/4*np.sqrt(np.abs(X)))

def inplace_m_arcsinh_derivative(Z, delta):
```
Apply the derivative of the hyperbolic $m$-arcsinh function.

It exploits the fact that the derivative is a simple function of the output value from the hyperbolic $m$-arcsinh.

Parameters

$Z : \{\text{array-like}, \text{sparse matrix}\}, \text{shape} (\text{n_samples}, \text{n_features})$

The data which were output from the hyperbolic $m$-arcsinh activation function during the forward pass.

delta : \{\text{array-like}\}, \text{shape} (\text{n_samples}, \text{n_features})

The back-propagated error signal to be modified in place.

```
delta *= (np.sqrt(np.abs(Z)) / (12 * np.sqrt(Z**2+1))
+ (Z * np.arcsinh(Z)) / (24 * np.abs(Z)**(3/2)))
```

classifier = MLPClassifier(activation='m_arcsinh',
                          random_state=1, max_iter=300)

2.4 Performance evaluation

The accuracy of the SVM and MLP using different kernel and activation functions respectively, as described in 2.3 and 2.4 on the datasets outlined in 2.1, was evaluated via the 'accuracy_score' available in 'scikit-learn' (Pedregosa et al., 2011) from 'sklearn.metrics'. The reliability of such classifiers was assessed via the weighted average of the precision, recall and F1-score computed via the 'classification_report', also available in 'scikit-learn' (Pedregosa et al., 2011) from 'sklearn.metrics'.

To understand what classification accuracy and reliability are, and how they can be evaluated, please refer to the following studies: (Parisi et al., 2018a), (Parisi et al., 2018b), (Parisi et al., 2020), (Parisi and RaviChandran, 2020).

Moreover, the computational cost of the classifiers, to quantify the impact of using different kernel and activation functions, was assessed via the training time in seconds. Experiments were run on an AMD E2-9000 Radeon R2 processor, 1.8 GHz and 4 GB DDR4 RAM.

3. Results

Experimental results demonstrate the competitiveness of the proposed $m$-arcsinh kernel and activation function for SVM and MLP respectively, as being accurate, reliable, and computationally efficient, with the following classification performance and training time:

- For the MLP:
  - The best classification performance on 10 out of 15 datasets evaluated (Tables 2, 3, 5-7, and Tables 7, 9, 10, 12-14 in the Appendix).
− The 2nd highest classification performance on 4 out of 15 datasets evaluated (Tables 1 and 4, and Tables 8 and 11 in the Appendix).
− The fastest training time on 2 out of 15 datasets assessed (Tables 13 and 15 in the Appendix).
− The best classification performance and the fastest training time on 2 out of 15 datasets assessed (Tables 13 and 15 in the Appendix).

• For the SVM:

− The best classification performance on 2 out of 15 datasets assessed (Table 2, Table 14 in the Appendix).
− The 2nd highest classification performance on 5 out of 15 datasets evaluated (Tables 1, 3, 4, and Tables 12 and 13 in the Appendix).
− The fastest training time on 7 out of 15 datasets assessed (Tables 1, 3, 6, 7, and Tables 9, 11, 12 in the Appendix).
− The 2nd highest classification performance and the fastest training time on 2 out of 15 datasets evaluated (Tables 1 and 3).
Table 1. Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the Breast cancer Wisconsin (diagnostic) dataset (Wolberg et al., 1995) available in scikit-learn.

| Classifier | Kernel function | Training time (s) | Accuracy (0-1) | Weighted precision (0-1) | Weighted recall (0-1) | Weighted F1-score (0-1) |
|------------|-----------------|------------------|---------------|--------------------------|-----------------------|------------------------|
| SVM        | m-arcsinh (this study) | 0.007            | 0.97          | 0.97                     | 0.97                  | 0.97                   |
| SVM        | RBF             | 0.017            | 0.92          | 0.92                     | 0.92                  | 0.92                   |
| SVM        | Linear          | 1.312            | 0.98          | 0.98                     | 0.98                  | 0.98                   |
| SVM        | Poly            | 311.706          | 0.98          | 0.98                     | 0.98                  | 0.98                   |
| SVM        | Sigmoid         | 0.012            | 0.39          | 0.15                     | 0.39                  | 0.21                   |
| MLP        | m-arcsinh (this study) | 9.830            | 0.91          | 0.91                     | 0.91                  | 0.91                   |
| MLP        | Identity        | 3.124            | 0.92          | 0.92                     | 0.92                  | 0.92                   |
| MLP        | Logistic        | 3.638            | 0.92          | 0.92                     | 0.92                  | 0.92                   |
| MLP        | tanh            | 3.568            | 0.90          | 0.90                     | 0.90                  | 0.90                   |
| MLP        | ReLU            | 3.132            | 0.92          | 0.92                     | 0.92                  | 0.92                   |

Table 2. Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the OptDigits dataset (Kaynak, 1995) available at the University California Irvine (UCI) Machine Learning repository.

| Classifier | Function       | Training time (s) | Accuracy (0-1) | Weighted precision (0-1) | Weighted recall (0-1) | Weighted F1-score (0-1) |
|------------|---------------|------------------|---------------|--------------------------|-----------------------|------------------------|
| SVM        | m-arcsinh (this study) | 0.232            | 0.97          | 0.97                     | 0.97                  | 0.97                   |
| SVM        | RBF           | 0.525            | 0.98          | 0.98                     | 0.98                  | 0.98                   |
| SVM        | Linear        | 0.175            | 0.96          | 0.96                     | 0.96                  | 0.96                   |
| SVM        | Poly          | 0.180            | 0.98          | 0.98                     | 0.98                  | 0.98                   |
| SVM        | Sigmoid       | 2.384            | 0.71          | 0.75                     | 0.71                  | 0.72                   |
| MLP        | m-arcsinh (this study) | 53.586           | 0.98          | 0.98                     | 0.98                  | 0.98                   |
| MLP        | Identity      | 9.572            | 0.98          | 0.98                     | 0.98                  | 0.98                   |
| MLP        | Logistic      | 27.457           | 0.98          | 0.98                     | 0.98                  | 0.98                   |
| MLP        | tanh          | 15.750           | 0.98          | 0.98                     | 0.98                  | 0.98                   |
| MLP        | ReLU          | 14.254           | 0.98          | 0.98                     | 0.98                  | 0.98                   |

Table 3. Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the LFW people dataset (Huang et al., 2007) (Learned-Miller, 2014) available in scikit-learn.

| Classifier | Function       | Training time (s) | Accuracy (0-1) | Weighted precision (0-1) | Weighted recall (0-1) | Weighted F1-score (0-1) |
|------------|---------------|------------------|---------------|--------------------------|-----------------------|------------------------|
| SVM        | m-arcsinh (this study) | 0.083            | 0.83          | 0.84                     | 0.83                  | 0.83                   |
| SVM        | RBF           | 0.508            | 0.85          | 0.87                     | 0.85                  | 0.85                   |
| SVM        | Linear        | 0.230            | 0.78          | 0.80                     | 0.78                  | 0.79                   |
| SVM        | Poly          | 0.483            | 0.65          | 0.60                     | 0.60                  | 0.60                   |
| SVM        | Sigmoid       | 0.570            | 0.82          | 0.83                     | 0.82                  | 0.82                   |
| MLP        | m-arcsinh (this study) | 7.101            | 0.86          | 0.86                     | 0.86                  | 0.86                   |
| MLP        | Identity      | 6.225            | 0.84          | 0.84                     | 0.84                  | 0.84                   |
| MLP        | Logistic      | 7.892            | 0.85          | 0.85                     | 0.85                  | 0.84                   |
| MLP        | tanh          | 5.562            | 0.84          | 0.84                     | 0.84                  | 0.84                   |
| MLP        | ReLU          | 4.755            | 0.84          | 0.84                     | 0.84                  | 0.83                   |
Table 4. Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the Iris dataset (Anderson, 1936) (Fisher, 1936) available in scikit-learn.

| Classifier | Function       | Training time (s) | Accuracy (0-1) | Weighted precision (0-1) | Weighted recall (0-1) | Weighted F1-score (0-1) |
|------------|----------------|-------------------|----------------|--------------------------|-----------------------|-------------------------|
| SVM        | m-arcsinh (this study) | 0.002             | 0.93           | 0.95                     | 0.93                  | 0.93                    |
| SVM        | RBF            | 0.003             | 0.63           | 0.43                     | 0.63                  | 0.50                    |
| SVM        | Linear         | 0.001             | 0.97           | 0.97                     | 0.97                  | 0.97                    |
| SVM        | Poly           | 0.003             | 0.33           | 0.11                     | 0.33                  | 0.17                    |
| SVM        | Sigmoid        | 0.002             | 0.50           | 0.43                     | 0.50                  | 0.40                    |
| MLP        | m-arcsinh (this study) | 2.357             | 0.90           | 0.93                     | 0.90                  | 0.90                    |
| MLP        | Identity       | 0.707             | 0.93           | 0.95                     | 0.93                  | 0.93                    |
| MLP        | Logistic       | 1.551             | 0.93           | 0.95                     | 0.93                  | 0.93                    |
| MLP        | tanh           | 0.939             | 0.93           | 0.95                     | 0.93                  | 0.93                    |
| MLP        | ReLU           | 1.344             | 0.93           | 0.95                     | 0.93                  | 0.93                    |

Table 5. Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the Heart failure clinical records dataset (Chicco and Jurman, 2020) available at the University California Irvine (UCI) Machine Learning repository.

| Classifier | Function       | Training time (s) | Accuracy (0-1) | Weighted precision (0-1) | Weighted recall (0-1) | Weighted F1-score (0-1) |
|------------|----------------|-------------------|----------------|--------------------------|-----------------------|-------------------------|
| SVM        | m-arcsinh (this study) | 1.285             | 0.88           | 0.90                     | 0.88                  | 0.89                    |
| SVM        | RBF            | 0.007             | 0.78           | 0.61                     | 0.78                  | 0.69                    |
| SVM        | Linear         | 48.287            | 0.89           | N/A                      | N/A                   | N/A                     |
| SVM        | Poly           | Did not converge  | N/A            | N/A                      | N/A                   | N/A                     |
| SVM        | Sigmoid        | 0.005             | 0.76           | 0.61                     | 0.78                  | 0.69                    |
| MLP        | m-arcsinh (this study) | 0.013             | 0.78           | 0.61                     | 0.78                  | 0.69                    |
| MLP        | Identity       | 0.023             | 0.78           | 0.61                     | 0.78                  | 0.69                    |
| MLP        | Logistic       | 0.011             | 0.78           | 0.61                     | 0.78                  | 0.69                    |
| MLP        | tanh           | 0.010             | 0.78           | 0.61                     | 0.78                  | 0.69                    |
| MLP        | ReLU           | 0.016             | 0.78           | 0.61                     | 0.78                  | 0.69                    |

Table 6. Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the Parkinsons dataset available at the University California Irvine (UCI) Machine Learning repository (Little et al., 2007).

| Classifier | Function       | Training time (s) | Accuracy (0-1) | Weighted precision (0-1) | Weighted recall (0-1) | Weighted F1-score (0-1) |
|------------|----------------|-------------------|----------------|--------------------------|-----------------------|-------------------------|
| SVM        | m-arcsinh (this study) | 0.005             | 0.79           | 0.78                     | 0.79                  | 0.79                    |
| SVM        | RBF            | 0.005             | 0.77           | 0.82                     | 0.77                  | 0.78                    |
| SVM        | Linear         | 0.182             | 0.87           | 0.92                     | 0.87                  | 0.88                    |
| SVM        | Poly           | 5.911             | 0.82           | 0.83                     | 0.82                  | 0.82                    |
| SVM        | Sigmoid        | 0.005             | 0.77           | 0.59                     | 0.77                  | 0.67                    |
| MLP        | m-arcsinh (this study) | 0.008             | 0.77           | 0.59                     | 0.77                  | 0.67                    |
| MLP        | Identity       | 0.009             | 0.77           | 0.59                     | 0.77                  | 0.67                    |
| MLP        | Logistic       | 0.016             | 0.77           | 0.59                     | 0.77                  | 0.67                    |
| MLP        | tanh           | 0.016             | 0.77           | 0.59                     | 0.77                  | 0.67                    |
| MLP        | ReLU           | 0.001             | 0.77           | 0.59                     | 0.77                  | 0.67                    |
Table 7. Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the Haberman survival dataset (Lim, 1999) available at the University California Irvine (UCI) Machine Learning repository.

| Classifier | Function | Training time (s) | Accuracy (0-1) | Weighted precision (0-1) | Weighted recall (0-1) | Weighted F1-score (0-1) |
|------------|----------|------------------|---------------|--------------------------|----------------------|------------------------|
| SVM        | m-arcsinh (this study) | 0.004            | 0.77          | 0.77                     | 0.77                 | 0.77                   |
| SVM        | RBF      | 0.004            | 0.79          | 0.78                     | 0.79                 | 0.79                   |
| SVM        | Linear   | 0.014            | 0.79          | 0.77                     | 0.79                 | 0.78                   |
| SVM        | Poly     | 0.010            | 0.77          | 0.77                     | 0.77                 | 0.77                   |
| SVM        | Sigmoid  | 0.005            | 0.82          | 0.82                     | 0.82                 | 0.74                   |
| MLP        | m-arcsinh (this study) | 1.219            | 0.76          | 0.77                     | 0.76                 | 0.76                   |
| MLP        | Identity | 1.095            | 0.76          | 0.77                     | 0.76                 | 0.76                   |
| MLP        | Logistic | 0.957            | 0.76          | 0.77                     | 0.76                 | 0.76                   |
| MLP        | tanh     | 0.912            | 0.76          | 0.77                     | 0.76                 | 0.76                   |
| MLP        | ReLU     | 0.974            | 0.76          | 0.77                     | 0.76                 | 0.76                   |

4. Discussion

As demonstrated by the competitive results obtained on the 15 datasets evaluated, especially those in Tables 2, 3, 5-7 and Tables 9, 10, 12-14 in the Appendix for the MLP, Tables 1, 3-5, and Tables 12-14 in the Appendix for the SVM, the m-arcsinh is deemed a suitable kernel and activation function for SVM and MLP respectively. In fact, its reliability was high, as quantified via appropriate metrics in 2.4, and better than some gold standard functions, e.g., considering Table 1 with the F1-score of the SVM using m-arcsinh being 0.97 as opposed to that of the SVM using RBF or sigmoid being 0.92 and 0.21 respectively. Moreover, its computational efficiency was generally high, e.g., considering Table 1 with the training time of the SVM leveraging m-arcsinh being only 0.007 seconds as compared to that of the SVM using linear or polynomial kernel being 1.312 and 311.706 seconds. Therefore, the m-arcsinh demonstrates that it is possible for a function to be generalised as a kernel and activation function concurrently and the mathematical formulation of such a function does not have to be sophisticated at all. As a reliable and computationally efficient function, the m-arcsinh is thus deemed a new gold standard kernel and activation function for SVM and MLP, freely available in scikit-learn.

5. Conclusion

m-arcsinh in scikit-learn provides a function in supervised ML that serves as a kernel for SVM and activation for MLP for classification. It is a fast and stable kernel and activation function, thus being a competitive candidate amongst the available gold standard functions for SVM and MLP in scikit-learn. Since it is made freely available, open source, on the Python and scikit-learn ecosystems, it adds to the choices that both academia and industry can have when selecting or optimising for kernel and activation functions for SVM and MLP respectively. Importantly, the proposed algorithm, being computationally efficient
and reliable, and written in a high-level programming language (Python), can be leveraged as a part of ML-based pipelines in specific use cases, wherein high accuracy and reliability need to be achieved, whilst powerful computational hardware may not always be available, such as in the healthcare sector, including small clinics. Future work involves adapting this function to benefit deep neural networks too.

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Appendix

In this appendix, as mentioned in the ‘Results’ section of this article, further results are provided in support of the proposed m-arcsinh kernel and activation function for SVM and MLP, implemented in Python and made freely available in scikit-learn, in Tables 8-15 on datasets from both scikit-learn and the UCI ML repository.

**Table 8.** Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the Handwritten Digits dataset (Alpaydin and Kaynak, 1998) available in scikit-learn.

| Classifier | Function                        | Training time (s) | Accuracy (0-1) | Weighted precision | Weighted recall | Weighted F1-score |
|------------|---------------------------------|-------------------|----------------|--------------------|-----------------|------------------|
| SVM        | m-arcsinh (this study)          | 0.037             | 0.95           | 0.95               | 0.95            | 0.95             |
| SVM        | RBF                             | 0.116             | 0.97           | 0.97               | 0.97            | 0.97             |
| SVM        | Linear                          | 0.033             | 0.93           | 0.93               | 0.93            | 0.93             |
| SVM        | Poly                            | 0.043             | 0.95           | 0.95               | 0.95            | 0.95             |
| SVM        | Sigmoid                         | 0.332             | 0.68           | 0.69               | 0.68            | 0.66             |
| MLP        | m-arcsinh (this study)          | 28.650            | 0.92           | 0.92               | 0.92            | 0.92             |
| MLP        | Identity                        | 5.452             | 0.91           | 0.91               | 0.91            | 0.91             |
| MLP        | Logistic                        | 14.182            | 0.94           | 0.94               | 0.94            | 0.93             |
| MLP        | tanh                            | 7.258             | 0.93           | 0.93               | 0.93            | 0.93             |
| MLP        | ReLU                            | 7.834             | 0.92           | 0.92               | 0.92            | 0.92             |

**Table 9.** Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the Wine dataset (Forina et al., 1991) available in scikit-learn.

| Classifier | Function                        | Training time (s) | Accuracy (0-1) | Weighted precision | Weighted recall | Weighted F1-score |
|------------|---------------------------------|-------------------|----------------|--------------------|-----------------|------------------|
| SVM        | m-arcsinh (this study)          | 0.003             | 0.89           | 0.89               | 0.89            | 0.89             |
| SVM        | RBF                             | 0.003             | 0.72           | 0.77               | 0.72            | 0.72             |
| SVM        | Linear                          | 0.162             | 0.94           | 0.95               | 0.94            | 0.94             |
| SVM        | Poly                            | 0.094             | 0.97           | 0.97               | 0.97            | 0.97             |
| SVM        | Sigmoid                         | 0.003             | 0.31           | 0.09               | 0.31            | 0.14             |
| MLP        | m-arcsinh (this study)          | 0.008             | 0.72           | 0.77               | 0.72            | 0.72             |
| MLP        | Identity                        | 0.016             | 0.72           | 0.77               | 0.72            | 0.72             |
| MLP        | Logistic                        | 0.008             | 0.72           | 0.77               | 0.72            | 0.72             |
| MLP        | tanh                            | 0.001             | 0.72           | 0.72               | 0.72            | 0.72             |
| MLP        | ReLU                            | 0.008             | 0.72           | 0.77               | 0.72            | 0.72             |
Table 10. Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the SPECF dataset (Cios et al., 2001) available at the University California Irvine (UCI) Machine Learning repository.

| Classifier | Function             | Training time (s) | Accuracy (0-1) | Weighted precision (0-1) | Weighted recall (0-1) | Weighted F1-score (0-1) |
|------------|----------------------|-------------------|----------------|---------------------------|-----------------------|------------------------|
| SVM        | m-arcsinh (this study) | 0.004             | 0.91           | 0.91                      | 0.91                  | 0.91                   |
| SVM        | RBF                  | 0.003             | 0.98           | 0.98                      | 0.97                  | 0.97                   |
| SVM        | Linear               | 0.004             | 1.00           | 1.00                      | 1.00                  | 1.00                   |
| SVM        | Poly                 | 0.003             | 1.00           | 1.00                      | 1.00                  | 1.00                   |
| SVM        | Sigmoid              | 0.003             | 0.50           | 0.25                      | 0.50                  | 0.33                   |
| MLP        | m-arcsinh (this study) | 0.047             | 0.54           | 0.76                      | 0.54                  | 0.41                   |
| MLP        | Identity             | 0.080             | 0.54           | 0.76                      | 0.54                  | 0.41                   |
| MLP        | Logistic             | 0.043             | 0.54           | 0.76                      | 0.54                  | 0.41                   |
| MLP        | tanh                 | 0.078             | 0.54           | 0.76                      | 0.54                  | 0.41                   |
| MLP        | ReLU                 | 0.096             | 0.54           | 0.76                      | 0.54                  | 0.41                   |

Table 11. Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the German Statlog credit data (Hofmann, 1994) available at the University California Irvine (UCI) Machine Learning repository.

| Classifier | Function             | Training time (s) | Accuracy (0-1) | Weighted precision (0-1) | Weighted recall (0-1) | Weighted F1-score (0-1) |
|------------|----------------------|-------------------|----------------|---------------------------|-----------------------|------------------------|
| SVM        | m-arcsinh (this study) | 0.023             | 0.70           | 0.74                      | 0.69                  | 0.71                   |
| SVM        | RBF                  | 0.043             | 0.71           | 0.75                      | 0.71                  | 0.73                   |
| SVM        | Linear               | 0.031             | 0.71           | 0.75                      | 0.71                  | 0.73                   |
| SVM        | Sigmoid              | 0.028             | 0.72           | 0.75                      | 0.72                  | 0.73                   |
| MLP        | m-arcsinh (this study) | 12.895            | 0.79           | 0.78                      | 0.79                  | 0.78                   |
| MLP        | Identity             | 1.328             | 0.79           | 0.78                      | 0.79                  | 0.78                   |
| MLP        | Logistic             | 7.189             | 0.80           | 0.79                      | 0.80                  | 0.79                   |
| MLP        | tanh                 | 6.769             | 0.79           | 0.78                      | 0.79                  | 0.78                   |
| MLP        | ReLU                 | 5.459             | 0.79           | 0.77                      | 0.79                  | 0.78                   |

Table 12. Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the Olivetti faces dataset (Roweis, 2017) available in scikit-learn.

| Classifier | Function             | Training time (s) | Accuracy (0-1) | Weighted precision (0-1) | Weighted recall (0-1) | Weighted F1-score (0-1) |
|------------|----------------------|-------------------|----------------|---------------------------|-----------------------|------------------------|
| SVM        | m-arcsinh (this study) | 0.143             | 0.91           | 0.91                      | 0.91                  | 0.90                   |
| SVM        | RBF                  | 1.452             | 0.31           | 0.28                      | 0.31                  | 0.27                   |
| SVM        | Linear               | 1.124             | 0.99           | 0.99                      | 0.99                  | 0.99                   |
| SVM        | Poly                 | 1.071             | 0.85           | 0.85                      | 0.85                  | 0.83                   |
| SVM        | Sigmoid              | 1.364             | 0.00           | 0.00                      | 0.00                  | 0.00                   |
| MLP        | m-arcsinh (this study) | 105.341           | 0.75           | 0.78                      | 0.75                  | 0.75                   |
| MLP        | Identity             | 109.109           | 0.75           | 0.78                      | 0.75                  | 0.75                   |
| MLP        | Logistic             | 94.982            | 0.75           | 0.78                      | 0.75                  | 0.75                   |
| MLP        | tanh                 | 103.759           | 0.75           | 0.78                      | 0.75                  | 0.75                   |
| MLP        | ReLU                 | 104.581           | 0.75           | 0.78                      | 0.75                  | 0.75                   |
Table 13. Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the Pen-based handwritten digits recognition dataset (Alpaydin and Alimoglu, 1998) available at the University California Irvine (UCI) Machine Learning repository.

| Classifier | Function         | Training time (s) | Accuracy (0-1) | Weighted precision (0-1) | Weighted recall (0-1) | Weighted F1-score (0-1) |
|------------|------------------|-------------------|----------------|--------------------------|-----------------------|------------------------|
| SVM        | m-arcsinh (this study) | 0.728             | 0.99           | 0.99                     | 0.99                   | 0.99                   |
| SVM        | RBF              | 2.922             | 1.00           | 1.00                     | 1.00                   | 1.00                   |
| SVM        | Linear           | 4.651             | 0.99           | 0.99                     | 0.99                   | 0.99                   |
| SVM        | Poly             | 0.196             | 1.00           | 1.00                     | 1.00                   | 1.00                   |
| SVM        | Sigmoid          | 3.024             | 0.13           | 0.06                     | 0.13                   | 0.06                   |
| MLP        | m-arcsinh (this study) | 17.736            | 1.00           | 1.00                     | 1.00                   | 1.00                   |
| MLP        | Identity         | 18.692            | 1.00           | 1.00                     | 1.00                   | 1.00                   |
| MLP        | Logistic         | 18.268            | 1.00           | 1.00                     | 1.00                   | 1.00                   |
| MLP        | tanh             | 20.490            | 1.00           | 1.00                     | 1.00                   | 1.00                   |
| MLP        | ReLU             | 19.362            | 1.00           | 1.00                     | 1.00                   | 1.00                   |

Table 14. Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the Wireless Indoor Localization dataset (Bhatt, 2005) (Rohra et al., 2017) available at the University California Irvine (UCI) Machine Learning repository.

| Classifier | Function         | Training time (s) | Accuracy (0-1) | Weighted precision (0-1) | Weighted recall (0-1) | Weighted F1-score (0-1) |
|------------|------------------|-------------------|----------------|--------------------------|-----------------------|------------------------|
| SVM        | m-arcsinh (this study) | 0.022             | 0.99           | 0.99                     | 0.99                   | 0.99                   |
| SVM        | RBF              | 0.015             | 0.99           | 0.99                     | 0.99                   | 0.99                   |
| SVM        | Linear           | 0.021             | 0.99           | 0.99                     | 0.99                   | 0.99                   |
| SVM        | Poly             | 0.038             | 0.99           | 0.99                     | 0.99                   | 0.99                   |
| SVM        | Sigmoid          | 0.081             | 0.21           | 0.05                     | 0.21                   | 0.07                   |
| MLP        | m-arcsinh (this study) | 5.870             | 0.98           | 0.98                     | 0.98                   | 0.98                   |
| MLP        | Identity         | 4.767             | 0.98           | 0.98                     | 0.98                   | 0.98                   |
| MLP        | Logistic         | 4.855             | 0.98           | 0.98                     | 0.98                   | 0.98                   |
| MLP        | tanh             | 4.615             | 0.98           | 0.98                     | 0.98                   | 0.98                   |
| MLP        | ReLU             | 6.343             | 0.98           | 0.98                     | 0.98                   | 0.98                   |

Table 15. Results on performance evaluation of baseline (non-optimised) Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) in scikit-learn with different kernel and activation functions respectively, including the proposed m-arcsinh function. The performance of such classifiers was evaluated on the Breast Cancer Coimbra dataset (Patrício et al., 2018) available at the University California Irvine (UCI) Machine Learning repository.
| Classifier | Function | Training time (s) | Accuracy (0-1) | Weighted precision (0-1) | Weighted recall (0-1) | Weighted F1-score (0-1) |
|------------|----------|------------------|----------------|--------------------------|-----------------------|-------------------------|
| SVM        | m-arcsinh (this study) | 0.005            | 0.71           | 0.71                     | 0.71                  | 0.71                    |
| SVM        | RBF      | 0.003            | 0.71           | 0.72                     | 0.71                  | 0.70                    |
| SVM        | Linear   | 0.726            | 0.75           | 0.75                     | 0.75                  | 0.75                    |
| SVM        | Poly     | 83.401           | 0.79           | 0.79                     | 0.79                  | 0.79                    |
| SVM        | Sigmoid  | 0.003            | 0.46           | 0.21                     | 0.46                  | 0.29                    |
| MLP        | m-arcsinh (this study) | 0.001            | 0.46           | 0.21                     | 0.46                  | 0.29                    |
| MLP        | Identity | 0.017            | 0.46           | 0.21                     | 0.46                  | 0.29                    |
| MLP        | Logistic | 0.016            | 0.46           | 0.21                     | 0.46                  | 0.29                    |
| MLP        | tanh     | 0.001            | 0.46           | 0.21                     | 0.46                  | 0.29                    |
| MLP        | ReLU     | 0.001            | 0.46           | 0.21                     | 0.46                  | 0.29                    |
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