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A Novel Approach to Disqualify Datasets Using Accumulative Statistical Spread Map with Neural Networks (ASSM-NN)

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Abstract

A novel approach to detect and filter out an unhealthy dataset from a matrix of datasets is developed, tested, and proved. The technique employs a new type of self organizing map called Accumulative Statistical Spread Map (ASSM) to establish the destructive and negative effect a dataset will have on the rest of the matrix if stayed within that matrix. The ASSM is supported by training a neural network engine, which will determine which dataset is responsible for its inability to learn, classify and predict. The carried out experiments proved that a neural system was not able to learn in the presence of such an unhealthy dataset that possessed some deviated characteristics, even though it was produced under the same conditions and through the same process as the rest of the datasets in the matrix, and hence, it should be disqualified, and either removed completely or transferred to another matrix. Such novel approach is very useful in pattern recognition of datasets and features that do not belong to their source and could be used as an effective tool to detect suspicious activities in many areas of secure filing, communication and data storage.

Keywords

Pattern Recognition, Informatics, Neural Networks, Data Mining, Classification, Prediction, Statistics

1. Introduction

In general, many neural networks applications are concerned with analyzing issues related to pattern recognition by using a supervised training method with training datasets. This will achieve and inference relationship between input patterns and output results [1]-[3].

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Neural Networks offers several algorithms and establishes models using data. Before applying any of the built-in functions for training, it is important to check that the data is reasonable, as good models can be obtained from poor or insufficient data. There is no specific procedure yet that can be used to test the quality or homogeneity and coherence of the data [4]-[6].

One way to check for quality is to view graphical representations of the data in question in the hope of selecting a reasonable subset while eliminating problematic parts. In examining the data for a classification problem, some reasonable points should be looked at, such as:

a) Equal representation of classes by datasets;

b) The presence of dissimilar datasets from the rest or neighboring values.

In supervised training, parameters such as weights and bias matrices for the neural network are used in order to classify all patterns in the training datasets. Larger training datasets are expected to reduce the overall error and error rate. However, it is a challenging task to produce a neural network that will be able to accommodate all patterns in a large training dataset, due to some patterns are difficult to classify. Even if network layers and neurons are modified, there are still some problems in pattern classification despite the lengthy training process [7]-[10].

The probability of occurrence of these patterns is expected to increase as a function of the size of the training dataset. Hence, the neural network will fail to recognize a pattern that approximates to one of the misclassified patterns. Also, if a new pattern is employed, which approximates to one of the misclassified patterns in the old training dataset, the neural network will not be able to classify it, and it will become a new misclassified; thus, the error rate will increase [11]-[14].

In this paper, a new approach catching and isolating such patterns is presented. The approach uses a new Accumulative Statistical Spread Map (ASSM) to initially establish the coherence of the patterns under consideration, and will not cause a misclassification in the neural network, and then when the status is established, the neural structure is used to determine which of the datasets and patterns is causing such misclassification and raising the error rate. Thus, such a neural network structure can be used as a filter and isolator with the Accumulative Statistical Spread Map used to determine which part or parts of the datasets is causing the problem. All the matrices of weights and biases are kept in the order that originally set from the training process throughout the testing process. Moreover, analysis results are used to control the updating process for new patterns.

2. Methodology

Two datasets that belong to the same general parent category are used in the experimental process to prove the concept. Same rules applied to produce the sets; hence, many general common features exist between them. The post processed datasets obtained using the ASSM approach with groups and subgroups produced to show two aspects:

a) If the datasets that the patterns represent belong to the same main group;

b) If there are signs that there will be a conflict in using them together, as one of them has an undesirable effect.

If the result in b is a confirmation, then a neural network algorithm is used to determine which one of the datasets and their patterns is the unhealthy one by carrying out the following steps:

1) Training and testing the considered datasets according to:

a) Dataset 1;

b) Dataset 2;

c) Combined Datasets 1 & 2;

2) Reporting margins of errors covering all three combinations of training;

3) Noticing the pattern that is least affected and classifying it as the unhealthy pattern.

The sorting algorithm is based on the expressions in Equations (1) and (2):

$$Category_i = \underset{1}{\overset{n}{f}}\left(Token_j\right) \tag{1}$$

$$Input_{ASSM} = \sum_{i=1}^{n} Token_j \tag{2}$$

where

f: Correlation function between the Tokens;

n: Range of classification;

j: Range of Tokens (in this work *j* = 4);

The ASSM carries out initial re-organization and sorting by correlation according to Equation (3), before it produces the final output:

$$ASSM_{Organization} = Corr\left(Category_i, Input_{ASSM}\right) \tag{3}$$

3. Results

Table 1 and **Table 2** show the used and categorized Datasets 1 and 2. These Datasets are used in the experimental process.

Table 1. Initial categorization results obtained for dataset 1.

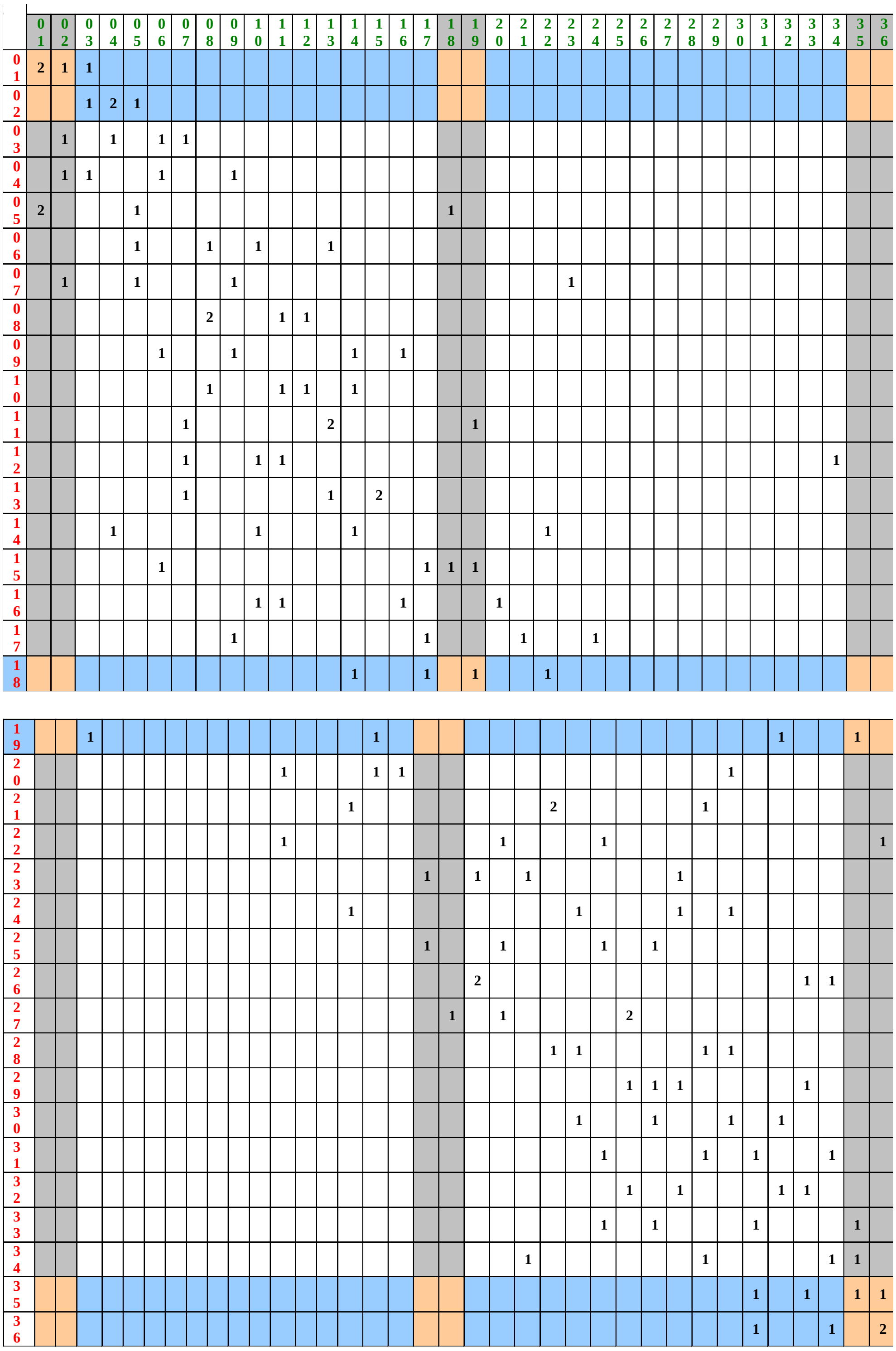
Category	$Token_1$	$Token_2$	$Token_3$	$Token_4$
1348	2	3	1	1
1935	4	5	3	4
2346	6	4	7	2
2470	9	6	2	3
2769	1	1	5	18
3698	13	8	10	5
3815	5	2	9	23
5071	11	12	8	8
5167	16	9	14	6
6099	8	11	12	14
6247	19	7	13	13
6851	7	10	11	34
7367	15	13	15	7
7418	14	22	4	10
8932	18	19	6	17
9190	10	16	20	11
10,405	24	17	21	9
10,934	22	14	17	19
11,527	3	32	35	16
12,024	17	30	16	12
12,854	23	15	23	29
13,000	12	25	36	21
13,381	20	18	22	28
14,056	30	24	28	15
14,242	25	21	18	27
14,336	33	20	32	20
14,636	21	26	19	26
15,747	29	23	30	24
16,215	26	28	27	33
16,280	32	27	24	30
17,255	34	29	25	31
17,817	28	33	26	32
18,087	27	35	31	25
19,032	35	34	29	22
19,180	36	31	33	35
20,362	31	36	34	36

Table 2. Initial categorization results obtained for dataset 2.

Category	$Token_1$	$Token_2$	$Token_3$	$Token_4$
915	1	1	1	1
2258	3	3	2	3
2505	2	2	3	4
3754	7	7	5	2
5358	4	8	7	5
6869	11	6	8	6
7131	10	9	4	17
7591	6	5	14	38
8972	26	4	32	37
9519	8	10	10	10
11,305	5	11	26	25
11,775	13	12	11	28
12,222	19	13	17	8
13,227	14	16	21	29
13,240	25	15	12	36
13,245	17	20	9	27
13,313	18	22	22	7
13,786	15	21	13	24
13,933	22	18	20	20
14,233	20	19	38	15
14,356	31	14	27	9
14,379	12	23	37	14
14,879	16	25	16	31
14,993	35	27	6	33
15,250	9	28	31	35
15,718	21	26	39	16
16,511	39	24	24	22
16,700	40	17	15	26
17,639	38	29	18	18
17,700	27	31	30	34
17,769	34	30	35	12
17,829	28	32	36	13
18,029	23	36	33	39
18,499	32	33	25	23
18,735	36	35	23	11
18,742	37	34	34	40
19,016	24	36	40	21
19,243	29	37	29	32
19,942	30	39	28	30
21,144	33	40	19	19

4. Discussion and Conclusions

Figure 1 and **Figure 2** show Accumulative Statistical Spread Map (ASSM) for Datasets 1 and 2. The maps represent the correlated statistical features in both Dataset 1 and Dataset 2 in relation to the sequence numbers assigned to them due to sorting.



	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
01	2	1	1																																	
02			1	2	1																															
03		1		1		1	1																													
04		1	1			1			1																											
05	2				1													1																		
06					1			1		1			1																							
07		1			1				1														1													
08								2			1	1																								
09						1			1					1		1																				
10								1			1	1		1																						
11							1						2						1																	
12							1			1	1																							1		
13							1						1		2																					
14				1						1				1								1														
15						1											1	1	1																	
16										1	1					1				1																
17									1								1				1			1												
18														1			1		1			1														
19			1													1																1			1	
20												1				1	1													1						
21															1								2						1							
22												1									1				1											1
23																		1		1		1						1								
24															1									1				1		1						
25																		1			1				1		1									
26																				2													1	1		
27																			1		1					2										
28																							1	1					1	1						
29																										1	1	1					1			
30																								1			1			1		1				
31																									1				1		1			1		
32																										1		1				1	1			
33																									1		1				1				1	
34																						1							1					1	1	
35																															1		1		1	1
36																															1			1		2

Figure 1. ASSM-dataset 1.

	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
01	4																																							
02		1	3																																					
03		2	1	1																																				
04		1			1		2																																	
05				1	1		1	1																																
06						2		1			1																													
07				1					1	1							1																							
08					1	1								1																								1		
09				1																						1						1					1			
10								1		3																														
11					1						1														1	1														
12											1	1	1															1												
13								1					1				1		1																					
14														1		1					1								1											
15												1			1										1											1				
16									1								1			1							1													
17							1											1				2																		
18													1		1						1			1																
19																		1		2		1																		
20															1				1	1																		1		
21									1					1													1				1									
22												1		1									1														1			
23																2									1						1									
24						1																					1						1		1					
25									1																			1			1				1					
26																1					1					1													1	
27																						1		2															1	
28															1		1									1														1
29																		2											1									1		
30																											1			1	1			1						
31												1																		1				1	1					
32													1															1				1				1				
33																							1										1			1			1	
34																							1		1							1	1							
35											1												1												1	1				
36																																		2			1			1
37																					1			1												1				1
38																													2			1					1			
39																												1		2									1	
40																			2														1							1

Figure 2. ASSM-dataset 2.

From the maps, the following is realized:

1) The concentration of feature spread into the second and fourth quarters of the ASSM (counterclockwise);

2) The similarity in feature spread confirms that the two patterns representing Datasets 1 and 2 derive from similar source with common features.

Each ASSM is processed to produce clustered representation, as shown in **Figure 3** and **Figure 4**, in order to obtain a similar representation to genetic code. This is shown in groups 1 and 2.

$$\text{Dataset } 1 \rightarrow \{3, 5, 0, 0, 0\}, \{5, 45, 4, 6, 0\}, \{0, 4, 1, 2, 1\}, \{0, 6, 3, 48, 3\}, \{0, 0, 0, 4, 4\} \quad (1)$$

$$\text{Dataset } 2 \rightarrow \{5, 3, 0, 0, 0\}, \{3, 45, 5, 15, 0\}, \{0, 4, 1, 3, 0\}, \{0, 14, 2, 46, 6\}, \{0, 2, 0, 4, 2\} \quad (2)$$

From groups 1 and 2, the following is deduced:

1) The existence of inverted digits (features position swapping) between dataset 1 and dataset 2; Inverted digit values are expected to have a destructive effect on the system learning and classification process;

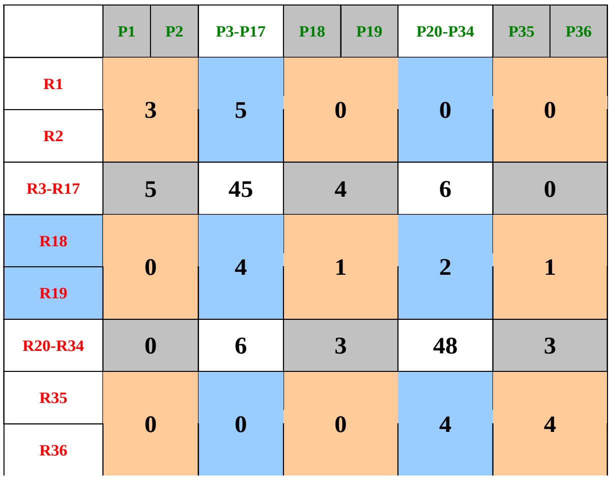
2) The presence of common features (features of similar value and position);

3) The presence of different features (features of different values in similar positions);

Placing the code groups into matrices 3 and 4 and carrying out row and column summation, shows the following:

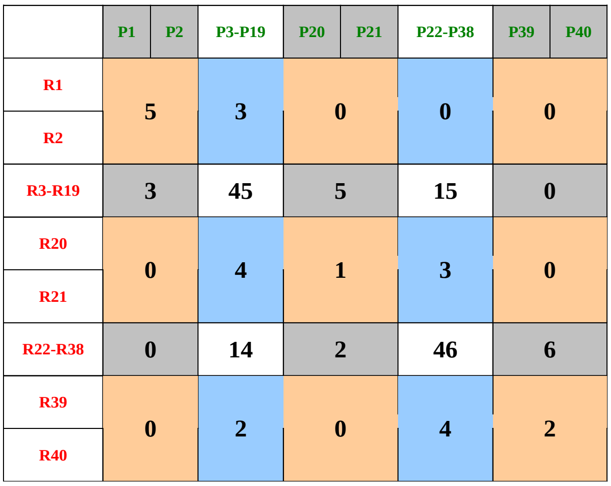
1) Each dataset follows an overall mathematical code that is specific to its representational pattern;

2) The symmetrical relationship between each Row and Column of each matrix. This is the result of using ASSM and indicates that both patterns belong to the same process;



	P1	P2	P3-P17	P18	P19	P20-P34	P35	P36
R1	3		5	0		0	0	
R2								
R3-R17	5		45	4		6	0	
R18	0		4	1		2	1	
R19								
R20-R34	0		6	3		48	3	
R35	0		0	0		4	4	
R36								

Figure 3. Clustered representation of dataset 1.



	P1	P2	P3-P19	P20	P21	P22-P38	P39	P40
R1	5		3	0		0	0	
R2								
R3-R19	3		45	5		15	0	
R20	0		4	1		3	0	
R21								
R22-R38	0		14	2		46	6	
R39	0		2	0		4	2	
R40								

Figure 4. Clustered representation of dataset 2.

3) The difference in the Column values with higher values appearing in Dataset 2 supports the evidence of Dataset 2 capability to overshadow Dataset 1 and negatively affect the overall learning and classification process.

$$\begin{bmatrix} 3 & 5 & 0 & 0 & 0 \\ 5 & 45 & 4 & 6 & 0 \\ 0 & 4 & 1 & 2 & 1 \\ 0 & 6 & 3 & 48 & 3 \\ 0 & 0 & 0 & 4 & 4 \end{bmatrix} \rightarrow \text{Row} = \{8, 60, 8, 60, 8\}, \text{Column} = \{8, 60, 8, 60, 8\} \tag{3}$$

$$\begin{bmatrix} 5 & 3 & 0 & 0 & 0 \\ 3 & 45 & 5 & 15 & 0 \\ 0 & 4 & 1 & 3 & 0 \\ 0 & 14 & 2 & 46 & 6 \\ 0 & 2 & 0 & 4 & 2 \end{bmatrix} \rightarrow \text{Row} = \{8, 68, 8, 68, 8\}, \text{Column} = \{8, 68, 8, 68, 8\} \tag{4}$$

The previous results indicate the presence of conflicting patterns, where one of them would cause a problem when used with the rest of similar patterns. To uncover the unhealthy pattern responsible for such condition, a back propagation neural algorithm is employed to train and test both datasets.

Table 3 and **Table 4** show the results for sorting, categorization, and neural networks training and testing

Table 3. Sorting, training, and testing of dataset 1.

Desired Output	Training Input				Actual Output	Sequential Number
Category	Token$_1$	Token$_2$	Token$_3$	Token$_4$	Category	
1348	2	3	1	1	1348	1
1935	4	5	3	4	1936	2
2346	6	4	7	2	2346	3
2470	9	6	2	3	2470	4
2769	1	1	5	18	2769	5
3698	13	8	10	5	3698	6
3815	5	2	9	23	3815	7
5071	11	12	8	8	5070	8
5167	16	9	14	6	5167	9
6099	8	11	12	14	6099	10
6247	19	7	13	13	6247	11
6851	7	10	11	34	6851	12
7367	15	13	15	7	7367	13
7418	14	22	4	10	7418	14
8932	18	19	6	17	8932	15
9190	10	16	20	11	9190	16
10,405	24	17	21	9	10,405	17
10,934	22	14	17	19	10,934	18
11,527	3	32	35	16	11,527	19
12,024	17	30	16	12	12,024	20
12,854	23	15	23	29	12,853	21
13,000	12	25	36	21	13,000	22
13,381	20	18	22	28	13,382	23
14,056	30	24	28	15	14,056	24
14,242	25	21	18	27	14,242	25
14,336	33	20	32	20	14,336	26
14,636	21	26	19	26	14,636	27
15,747	29	23	30	24	15,747	28
16,215	26	28	27	33	16,215	29
16,280	32	27	24	30	16,279	30
17,255	34	29	25	31	17,257	31
17,817	28	33	26	32	17,816	32
18,087	27	35	31	25	18,088	33
19,032	35	34	29	22	19,032	34
19,180	36	31	33	35	19,180	35
20,362	31	36	34	36	20,362	36

Table 4. Sorting, training, and testing of dataset 2.

Desired Output	Training Input				Actual Output	Sequential Number
Category	Token$_1$	Token$_2$	Token$_3$	Token$_4$	Category	
915	1	1	1	1	915	1
2258	3	3	2	3	2258	2
2505	2	2	3	4	2503	3
3754	7	7	5	2	3753	4
5358	4	8	7	5	5359	5
6869	11	6	8	6	6870	6
7131	10	9	4	17	7131	7
7591	6	5	14	38	7591	8
8972	26	4	32	37	8972	9
9519	8	10	10	10	9518	10
11,305	5	11	26	25	11,305	11
11,775	13	12	11	28	11,775	12
12,222	19	13	17	8	12,222	13
13,227	14	16	21	29	13,228	14
13,240	25	15	12	36	13,240	15
13,245	17	20	9	27	13,245	16
13,313	18	22	22	7	13,313	17
13,786	15	21	13	24	13,787	18
13,933	22	18	20	20	13,932	19
14,233	20	19	38	15	14,233	20
14,356	31	14	27	9	14,357	21
14,379	12	23	37	14	14,378	22
14,879	16	25	16	31	14,879	23
14,993	35	27	6	33	14,993	24
15,250	9	28	31	35	15,249	25
15,718	21	26	39	16	15,719	26
16,511	39	24	24	22	16,511	27
16,700	40	17	15	26	16,700	28
17,639	38	29	18	18	17,639	29
17,700	27	31	30	34	17,699	30
17,769	34	30	35	12	17,769	31
17,829	28	32	36	13	17,828	32
18,029	23	36	33	39	18,030	33
18,499	32	33	25	23	18,500	34
18,735	36	35	23	11	18,735	35
18,742	37	34	34	40	18,741	36
19,016	24	36	40	21	19,017	37
19,243	29	37	29	32	19,244	38
19,942	30	39	28	30	19,941	39
21,144	33	40	19	19	21,144	40

results for similarly processed datasets with the neural engine trained using dataset 1 in isolation from dataset 2, and dataset 2 in isolation from dataset 1 with RED Sequential Numbers pointing towards the records with difference between Actual and Desired data, while **Table 5** and **Table 6** show the results for the same datasets merged and sorted in relation to each other, and presented to the neural engine for training and testing.

From **Table 7** and **Table 8**, it is deduced that Dataset 2 prediction starts with larger initial error, and stays unaffected after merging with Dataset 2 as a training set. For Dataset 1 , the result is almost opposite, as its prediction starts with much smaller error and suffers large error increase after merging with Dataset 2 as a training set. This indicates a marked increase in the level of total pattern destruction and mutation due to effect of Dataset 2. So, Dataset 2 disabled the proper functionality of the Neural Structure and inhibited its performance.

The previous is supported by the following percentage errors appearing in **Table 9**, where it is clear that Dataset 2 is not affected by Dataset 1, while Dataset 1 is greatly and adversely affected by the presence of Dataset 2.

Table 5. Sorting, training, and testing of dataset 1 merged with dataset 2.

Desired Output	Training Input				Actual Output	Sequential Number
Category	Token$_1$	Token$_2$	Token$_3$	Token$_4$	Category	
1348	2	3	1	1	1296	1
1935	4	5	3	4	3429	2
2346	6	4	7	2	4491	3
2470	9	6	2	3	3457	4
2769	1	1	5	18	7253	5
3698	13	8	10	5	8636	6
3815	5	2	9	23	9810	7
5071	11	12	8	8	8437	8
5167	16	9	14	6	11,360	9
6099	8	11	12	14	12,265	10
6247	19	7	13	13	12,374	11
6851	7	10	11	34	8555	12
7367	15	13	15	7	12,036	13
7418	14	22	4	10	6917	14
8932	18	19	6	17	10,442	15
9190	10	16	20	11	13,997	16
10,405	24	17	21	9	13,697	17
10,934	22	14	17	19	13,817	18
11,527	3	32	35	16	16,206	19
12,024	17	30	16	12	14,843	20
12,854	23	15	23	29	14,189	21
13,000	12	25	36	21	15,584	22
13,381	20	18	22	28	14,495	23
14,056	30	24	28	15	16,788	24
14,242	25	21	18	27	15,914	25
14,336	33	20	32	20	16,770	26
14,636	21	26	19	26	16,520	27
15,747	29	23	30	24	17,338	28
16,215	26	28	27	33	17,574	29
16,280	32	27	24	30	18,014	30
17,255	34	29	25	31	18,664	31
17,817	28	33	26	32	18,961	32
18,087	27	35	31	25	20,231	33
19,032	35	34	29	22	20,904	34
19,180	36	31	33	35	19,395	35
20,362	31	36	34	36	19,886	36

Table 6. Sorting, training, and testing of dataset 2 merged with dataset 1.

Desired Output	Training Input				Actual Output	Sequential Number
Category	Token$_1$	Token$_2$	Token$_3$	Token$_4$	Category	
915	1	1	1	1	915	1
2258	3	3	2	3	2258	2
2505	2	2	3	4	2503	3
3754	7	7	5	2	3753	4
5358	4	8	7	5	5359	5
6869	11	6	8	6	6870	6
7131	10	9	4	17	7131	7
7591	6	5	14	38	7591	8
8972	26	4	32	37	8972	9
9519	8	10	10	10	9518	10
11,305	5	11	26	25	11,305	11
11,775	13	12	11	28	11,775	12
12,222	19	13	17	8	12,222	13
13,227	14	16	21	29	13,228	14
13,240	25	15	12	36	13,240	15
13,245	17	20	9	27	13,245	16
13,313	18	22	22	7	13,313	17
13,786	15	21	13	24	13,787	18
13,933	22	18	20	20	13,932	19
14,233	20	19	38	15	14,233	20
14,356	31	14	27	9	14,357	21
14,379	12	23	37	14	14,378	22
14,879	16	25	16	31	14,879	23
14,993	35	27	6	33	14,993	24
15,250	9	28	31	35	15,249	25
15,718	21	26	39	16	15,719	26
16,511	39	24	24	22	16,511	27
16,700	40	17	15	26	16,700	28
17,639	38	29	18	18	17,639	29
17,700	27	31	30	34	17,699	30
17,769	34	30	35	12	17,769	31
17,829	28	32	36	13	17,828	32
18,029	23	36	33	39	18,030	33
18,499	32	33	25	23	18,500	34
18,735	36	35	23	11	18,735	35
18,742	37	34	34	40	18,741	36
19,016	24	36	40	21	19,017	37
19,243	29	37	29	32	19,244	38
19,942	30	39	28	30	19,941	39
21,144	33	40	19	19	21,144	40

Table 7. Margin comparison-dataset 1.

Margin (Dataset 1)	
Before Combining	After Combining
0	52
1	1494
0	2145
0	987
0	4484
0	4938
0	5995
1	3366
0	6193
0	6166
0	6127
0	1704
0	4669
0	501
0	1510
0	4807
0	3292
0	2883
0	4679
0	2819
1	1335
0	2584
1	1114
0	2732
0	1672
0	2434
0	1884
0	1591
0	1359
1	1734
2	1409
1	1144
1	2144
0	1872
0	215
0	476

Table 8. Margin comparison dataset 2.

Margin (Dataset 2)	
Before Combining	After Combining
0	0
0	0
2	2
1	1
1	1
1	1
0	0
0	0
0	0
1	1
0	0
0	0
0	0
1	1
0	0
0	0
0	0
1	1
1	1
0	0
1	1
1	1
0	0
0	0
1	1
1	1
0	0
0	0
0	0
1	1
0	0
1	1
1	1
1	1
0	0
1	1
1	1
1	1
1	1
0	0

Table 9. Margin change for datasets 1 and 2.

Percentage Error (Dataset 1)		Percentage Error (Dataset 2)	
Before Combining	After Combining	Before Combining	After Combining
19.4	100	50	50
Percentage Increase in Error			
79.6		0	

In conclusion, the ASSM proved its capability to detect and filter out undesirable datasets, which would greatly assist optimizing the neural network structure. Such functionality is critical in facilitating both good neural network designs and isolating certain datasets to study their behavior and reach a conclusion regarding the causes behind such abnormalities. The ASSM can be very useful in Health and Medical applications, such as cases where tumors are involved.

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