A Cellular Automata based Classification Algorithm

Tuğba Usta[1], Enes Burak Dündar[2] and Emin Erkan Korkmaz[1]
[1]*Department of Computer Engineering, Yeditepe University, İstanbul, Turkey*
[2]*Department of Computer Engineering, Boğaziçi University, İstanbul, Turkey*

Keywords: Classification, Cellular Automata, Big Data.

Abstract: Data classification is a well studied problem where the aim is to identify the categories in the data based on a training set. Various machine learning methods have been utilized for the problem. On the other side, cellular automata have drawn the attention of researchers as the system provides a dynamic and a discrete model for computation. In this study a novel approach is proposed for the classification problem. The method is based on formation of classes in a cellular automata by the interaction of neighborhood cells. Initially, the training data instances are assigned to the cells of a cellular automaton. The state of a cell denotes the class assignment of that point in the instance space. At the beginning of the process, only the cells that have a data instance have class assignments. However, these class assignments are spread to the neighbor cells based on a rule inspired by the heat transfer process in nature. The experiments carried out denote that the model can identify the categories in the data and promising results have been obtained.

1 INTRODUCTION

Given a set of training examples $\{(x_1,l_1),(x_2,l_2),...(x_n,l_n)\}$, where x_i is a data instance represented as a feature vector and l_i is the corresponding class label for x_i, the classification task can be defined as inducing a function $f : X \rightarrow L$ where X is the instance space and L is the output space. The accuracy of the process is determined by using a separate test set. The f function can be considered as a separator in the instance space that can distinguish the categories in the data. Various techniques have been proposed and utilized for classification problems including decision trees, support vector machines or Bayesian approaches (Friedl and Brodley, 1997; Cortes and Vapnik, 1995; Cheeseman et al., 1988). Cellular Automata (CA) provides a means for computation based on a discrete system that is composed of interconnected cells. The Conway's Game of life is the most well known example for CA (Gardner, 1970). Other CA applications exist in the literature where CA have been mainly used as simulation tools for various disciplines (Ermentrout and Edelstein-Keshet, 1993; Hesselbarth and Göbel, 1991; Mai and Von Niessen, 1992; Margolus et al., 1986; Langton, 1984)

Classification techniques that utilize different types of CA have also been proposed in the literature. For instance in (Povalej et al., 2005), a Multiple Classifier System is proposed. In the study, an automaton is used to determine the set of appropriate classifiers for a specific problem. In (Esmaeilpour et al., 2012), a learning CA is proposed to extract the patterns in the raw data. The learning process that takes place in the automaton detects the frequently repeated patterns in the data.

The two studies mentioned above utilize CA in the classification process for different purposes. However, in (Kokol et al., 2004), the classification process is carried out by a CA. An energy function is utilized and the features of the dataset are associated with the columns of the CA. The energy value of a cell in a certain column denotes if a training sample is classified correctly or not. The learning is carried out by the interaction of the neighbor cells. The energy parameter and threshold values utilized in the study needs to be tuned for each dataset separately and this is a serious drawback for the study.

In this study, a stochastic cellular automata algorithm named as *SCA-classification* is proposed and the method classifies the data again by using a CA. At the beginning of the procedure, the elements in the training dataset are mapped to fixed cells in a CA. Then each cell is assigned a state number denoting the class label of the data instance it contains. Certainly, the empty cells will have no class assignments, initially. Then, by using the local interactions among the cells, the class labels are transferred to the other cells in the automaton. The process of spreading the class labels is inspired by the heat transfer process in nature. The CA cells that have a data instance are con-

Usta, T., Dündar, E. and Korkmaz, E.
A Cellular Automata based Classification Algorithm.
DOI: 10.5220/0007373001550162
In *Proceedings of the 8th International Conference on Pattern Recognition Applications and Methods (ICPRAM 2019)*, pages 155-162
ISBN: 978-989-758-351-3

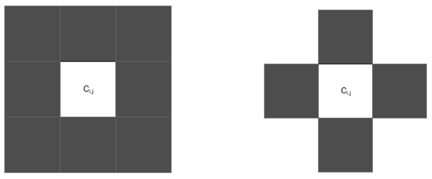
sidered as heat sources and they generate heat energy continuously. This energy is spread to the neighborhood cells and the regions that are close to the data instances warm up in the automaton. On the other side, a second rule is used which enables the heated cells to change their states. Hence, the cells without class assignments start to join different classes represented by different states in the automaton. In the end, the instance space represented by the automaton is categorized based on the classes that exist in the training data.

The idea of using heat propagation in a CA to perform certain kind of computations has been applied to the clustering problem in (Dündar and Korkmaz, 2018). Clustering is a also well studied problem where the process is carried out on unlabelled data, in an unsupervised manner. Even though a similar heat propagation approach is utilized in (Dündar and Korkmaz, 2018), the data is analyzed with a different algorithm in order to determine the clusters in the data. Hence, the two studies differ from each other especially in terms of the state transfer rule and the termination criteria utilized. The approach used in (Dündar and Korkmaz, 2018) forms different primitive clusters in the CA and then these primitive units are combined into larger clusters in order to obtain the final clustering of the dataset. In (Uzun et al., 2018), a similar approach has been proposed to solve the classification problem. However, this study utilizes a separate two dimensional CA for each class and each feature in the dataset is separately analyzed by the method.

The approach proposed in this study has also similarities with the method presented in (Fawcett, 2008). The authors utilize CA for the classification process in (Fawcett, 2008), too. However, they use a voting rule where a cell changes its state according to the majority class among its neighbors. In (Fawcett, 2008), it is noted that each cell is assigned to the class label of the nearest initial point in the CA according to *Manhattan Distance*. In our study, a different framework is utilized for changing the cell states. As noted above, the process is inspired from the heat transfer procedure in nature. This provides a different inductive bias where the structure of classes formed is dependent on the distribution of the data in the CA. Details about the differences between the two approaches can be found in section 3.

2 METHODOLOGY

Cellular Automata provide a dynamical system which is composed of regular cells. Each cell in the system can be in one of a predefined set of states and computation is carried out by updating the state values by some specific rules. These rules are defined based on the interaction of neighbor cells.



(a) Moore (b) Von Neumann

Figure 1: Neighborhood Types.

The two most commonly used neighborhood types in the model are the Moore neighborhood and Von Neumann neighborhood. In 2-dimensions, the center cell has 8 neighbors according to Moore neighborhood. As seen in Figure 1a, if the center cell is $C_{i,j}$, then all cells $C_{k,s}$ where $|i-k| \leq 1$ or $|j-s| \leq 1$ would be in the Moore neigborhood of the center cell. In a n dimensionsional CA, the center cell would have $3^n - 1$ neighbors. On the other side, the center cell has only 4 neighbors in 2 dimensions according to Von Neumann neighborhood. As seen in Figure 1b, if the center cell is $C_{i,j}$, then only the cells $C_{k,s}$ where $|i-k| = 1$ and $|j-s| = 0$ or $|i-k| = 0$ and $|j-s| = 1$ would be in the neigborhood. This time, in n dimensions, the center cell has $2*n$ neighbors. In Moore neighborhood, the number of neighbor cells increase exponentially based on the dimension, however this increase is linear in Von Neumann neighborhood. Therefore, Von Neumann neighborhood is used in this study.

2.1 Assigning Data Instances to CA Cells

The instances in the dataset have to be assigned to the cells of a CA at the beginning of the procedure. The CA utilized for the process would have n dimensions where n is determined by number of attributes in the dataset. The dataset is separated randomly into training (60%), test (20%) and validation (20%) sets initially. Certainly, the test set is utilized for determining the success rate after the training process is finished. The validation set is utilized for defining a termination criterion for the training phase (The details can be found in Section 2.4).

A data instance is assigned to a CA cell based on its attribute values. If the number of cells in dimension d is c and if the maximum and minimum values of the attribute associated for this dimension are A^d_{max} and A^d_{min} in the dataset, then in this dimension, the index of the cell (x_{i_d}) for a data instance x that has attribute value x^d_A, is calculated as given in Equation 1.

In this equation, the ceiling function is needed since the calculated indexes are integer values.

$$x_{i_d} = \left\lceil \frac{x_A^d - A_{min}^d}{(A_{max}^d - A_{min}^d)/c} \right\rceil \qquad (1)$$

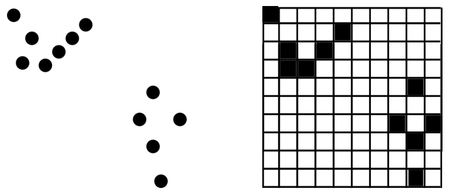

(a) A sample dataset (b) Data instances assigned to cells

Figure 2: Mapping process for 2-dimensional sample data.

An example mapping process is illustrated in Figure 2. In Figure 2a, a sample dataset distribution is presented. Then the data instances are mapped to the lattice according to attribute values in Figure 2b. Certainly, the cell indexes are calculated by using the Equation 1. The empty cells would not have any class assignment initially. As noted in the previous section, the class labels are spread in the CA by a method inspired from the heat transfer process in nature. The cells that contain data instances are considered as heat sources. The heat energy which is generated by these cells is transferred to other cells. Therefore, each cell has also an initial temperature value. The cells that contain data instances have fixed temperature 100°. The empty cells have 0° temperature at the beginning of the procedure. Two different rules are utilized in the classification process. The first rule transfers the heat energy produced by the heat sources in the automaton. The second rule enables the warmed empty cells to change their state. When these two rules are utilized on randomly chosen cells repeatedly, the class labels represented by the state values of the initial cells start to spread to the empty cells in the CA and it becomes possible to categorize the instance space represented by the CA. These two rules are presented in detail in the next two subsections.

2.2 Heat Transfer in CA

The heat transfer rule is given in algorithm 1. The input cell C in the algorithm is selected randomly from a selection set. The selection set consists of the cells with data instances and their neighbors initially. Then the neighbors of the selected cell are determined. If a neighbor does not exist in the selection list, it is also created and added to the data structure (which means it can be also selected for heat transfer procedure in the following steps). Then the average temperature of the selected cell and its neighbors is determined. Note that if the cell contains a data instance, its temperature is fixed (100°) and it is not updated by the procedure. However, if the cell is empty, its new temperature is set as the average value. What is more, the temperature of the neighborhood cells are also updated unless they contain a data instance.

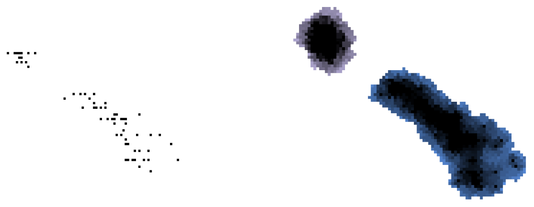

(a) Initial data distribution (b) Heat propagation

Figure 3: Heat propagation process.

The average temperature of all cells would have a tendency to be equalized with the above procedure. However, the heat sources constantly provide energy to the system and they do not cool down. This enables the regions with more data instances to be heated more compared to other regions in the CA. In Figure 3a, an example 2-dimensional dataset is given. Figure 3b presents the temperature values of CA cells after the above procedure is applied for a while on randomly chosen cells. Higher temperatures are denoted by darker tones in the figure. As expected, denser areas in the CA are heated more.

2.3 State Transfer

Note that, different classes in the data set are indicated by different state values in the CA. Initially, the non-empty cells have state values denoting the class label of the data instance that they contain. The state values of these non-empty cells are fixed and they are not changed by the procedure. However an empty cell can change its state based on its temperature. The empty cells can be converted to the states of neighbor cells if they are heated sufficiently.

The state transfer procedure is explained in Algorithm 2. Again a cell is selected randomly from the selection list. A cell can transfer its state to a neighbor state if the cell and the neighbor is heated sufficiently. As seen in the algorithm, if the temperature of the selected cell C is above the threshold (30°) and if the state of the cell is non-zero, then the neighbors of C are determined. Then all neighbors that have temperature above the threshold are transferred to the state of C. Note that the function is called recursively on the neighbor cells so that state values would spread rapidly in a heated region of the automaton.

Algorithm 1: Heat Transfer in CA.

```
1:  procedure HEAT–PROPAGATION(CELL C)
2:      $N \longleftarrow getNeighbour(C)$
3:      AverageTemperature = $calculateAverageTemperature(C,N)$
4:      if $empty(C)$ then
5:          $C_{temperature}$ = AverageTemperature
6:      end if
7:      for each Cell $K \in N$ do
8:          if $empty(K)$ then
9:              $K_{temperature}$ = AverageTemperature
10:         end if
11:     end for
12: end procedure
```

Algorithm 2: State Transfer in CA.

```
1:  procedure STATE –TANSFER(CELL C)
2:      if $((C_{state}! = 0)$ and $(C_{temperature} > threshold))$ then
3:          $N \longleftarrow getNeighbour(C)$
4:          for each cell $K \in N$ do
5:              if $((K_{state} == 0)$ and $(K_{temperature} > threshold))$ then
6:                  $K_{State} = C_{State}$
7:                  STATE–TRANSFER(K)
8:              end if
9:          end for
10:     end if
11: end procedure
```

2.4 The General Algorithm

The overall procedure is given in Algorithm 3. As seen in the algorithm, the training data is mapped to the CA and then a loop is started where the heat and state transfer procedures are repeatedly applied on randomly selected cells.

As mentioned in Section 2.1, a validation set is utilized in order to define a stopping criterion in the algorithm. Note that the initial class labels spread to empty cells with the state transfer procedure. However, the number of cells in the CA increases exponentially for high dimensional data, therefore it is not possible to create and assign a class label to all of the cells in the CA. A data structure initially including the cells that have training data instances and their neighbors is created. Then new neighbors are added to the selection list data structure as the heat propagates in the CA. The data instances in the validation set are used to determine if a sufficient coverage has been obtained for the classes in the CA. The algorithm is terminated when state transfer procedure assigns a class label to 95% of the cells with data instances from the validation set. Then the remaining 5% of the cells are assigned to the class label of the nearest class in the automaton. This procedure is denoted by the $DETERMINE - LABEL(K)$ method in the algorithm.

3 EXPERIMENTAL RESULTS

As noted in Section 1, the method presented in this study is similar to the approach presented in (Fawcett, 2008). In (Fawcett, 2008), a similar classification procedure is carried out by using CA. However, the class labels are spread in the CA based on a majority rule in this study. As noted in (Fawcett, 2008), this results each cell to be assigned to the class label of the closest cell that contains a data instance. It can be claimed that this is a strong bias that can result in undesired categorization of the input space. Consider the example dataset with two classes in Figure 4c. In this figure, one of the classes consists of only a few instances, whereas the other class contains a larger number of instances compared to the first one. With the rule utilized in (Fawcett, 2008), the instance space would be categorized into almost two equal size regions as seen in Figure 4b. This bias introduced by the method could be a serious drawback especially for noisy data.

In Figure 4a, the same dataset is classified by using SCA-classification. The bias introduced by the

Algorithm 3: The Overall Algorithm.

```
 1: procedure SCA–CLASSIFY(CELLULAR AUTOMATON CA, DATASET D)
 2:     $MAPDATA(CA, D_{train})$
 3:     int continue=1
 4:     int iteration=0
 5:     while (continue) do
 6:         Cell C=$getCellFromSelectionSet(CA)$
 7:         HEAT–PROPAGATION(C)
 8:         Cell C=$getCellFromSelectionSet(CA)$
 9:         STATE–TRANSFER(C)
10:         if iteration%1000 = 0 then
11:             continue = $ControlValidationPoints(CA, D_{validation})$
12:         end if
13:         iteration++
14:     end while
15:     $N \longleftarrow getNotAssignedClassList(CA, D_{validation})$
16:     for each cell $K \in N$ do
17:         DETERMINE–LABEL($K$)
18:     end for
19: end procedure
```

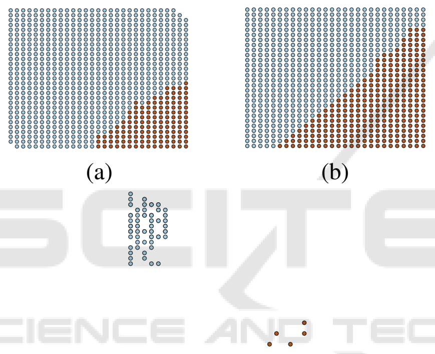


Figure 4: Comparison of classification approaches: SCA-classification(a), Manhattan distance classification(b), and Data distribution(c).

heat transfer procedure in the algorithm enables the denser class to spread to a larger area in the CA compared to the other class consisting of only a few elements. In (Fawcett, 2008), experimental results are reported only on five real-world datasets and the method is tested on datasets consisting of only 2 classes. We have the impression that the method is not applicable to multi-class real-world datasets. Therefore, we have decided to compare SCA-classification with other state of the art classification methods, instead of the approach presented in (Fawcett, 2008). The next subsection firstly presents the description of the datasets utilized in the experiments and then a comparison between SCA-classification and some other methods is presented.

3.1 SCA-classification on (UCI) Datasets

Experiments are carried out on 8 different datasets from UCI data repository (Newman and Merz, 1998). Table 1 presents the properties of the datasets utilized in the experiments. As seen in the table, datasets with different number of attributes and classes are selected for the experiments.

Correlation Based Feature Selection: method (Hall and Smith, 1998) have been applied on the datasets before the classification process in order to

Table 1: Datasets utilized in the experiments.

Dataset	# of Attributes	# of Classes	# of Instances
Iris	2	3	150
Banknote	2	2	1372
Glass	8	7	214
Heart	7	2	270
Australian	5	2	690
Haberman	2	2	306
Pima	2	2	768
Breast-wisc	9	2	699

Table 2: Experimental results for SCA-classification.

Dataset	Mean Success(%)	Best Solution(%)
Iris	95.00 ± 3.07	100.0
Banknote	88.76 ± 1.92	93.09
Glass	50.47 ± 6.50	65.12
Heart	78.15 ± 6.24	85.19
Australian	83.55 ± 3.04	89.13
Haberman	70.16 ± 4.03	75.81
Pima	69.68 ± 4.74	76.62
Breast-wisc	93.71 ± 2.36	97.86

reduce the dimensionality of the datasets. For the Iris dataset, *petal length* and *petal width*, for the Banknote dataset, 1st and 2nd attributes are selected by the method. Only the *Si* attribute is removed in the reduction process for the Glass dataset. Heart dataset has 13 attributes orginally. 7 attributes are selected which are *chest, resting electrocardiographic result, maximum heart rate archived, exercise induced angina, oldpeak, number of major vessels* and and *thal*. On the other side, the number of attributes are reduced from 14 to 5 for the Australian dataset. The attributes chosen by the method are the 5th, 8th, 10th , 13rd and 14th ones. The attributes *the year of operation* and *the number of positive nodes* are the selected ones for the Haberman dataset. For Pima dataset, the *plasma, body mass index, pedigree function* and *age* attributes are selected. Lastly, Breast-wisc dataset has 9 attributes originally. No attribute is removed for this dataset in the attribute reduction process. In Table 1, the remaining final number of attributes are presented.

In Table 2, the performance of SCA-classification is presented on the selected datasets. The results denote the accuracy on the test sets that are chosen randomly. The average performance is the mean of 10 different runs. The result of the best run is also presented in the table.

In Table 5, effects of different threshold values are denoted by conducting an experiments on the iris data. Obviously, it requires more time when threshold values are increased. Also, mean success slightly decreases for higher threshold values.

In Table 3, a set of synthetic datasets generated by *Gaussian Generator* (Handl, 2017) has been utilized in order to unveil the effect of number of classes and attributes on performace metrics: accuracy and runtime. When the number of classes in 2-dimensional datasets is steadily increased, accuracy decreases, since data instances belonging to different classes become closer. Also, runtime increases since the number of instances in the datasets increase with more classes. On the other side, the number of attributes do not have a significant effect on the metrics as seen in the table.

Table 3: Analysis of SCA-classification on synthetic datasets in terms of the number of clusters and attributes.

# of Attributes	# of Classes	Mean Success(%)	Mean Runtime(s)
2	5	99.94±0.06	0.55
2	10	99.75±0.25	0.93
2	15	98.24±1.40	1.47
2	20	95.86±1.60	2.01
2	25	89.13±3.59	2.71
2	30	85.80±1.49	4.28
3	5	100.0±0.00	0.93
4	5	99.84±0.12	1.91
5	5	100.0±0.00	1.58
6	5	100.0±0.00	11.16
7	5	100.0±0.00	87.72

In Table 4, the accuracy obtained by different classification methods on the same datasets is given. The results are collected from a set of studies in the literature and when a method is not applied to a dataset, this is denoted as ”-” in the table. It is not possible to claim that SCA-classification outperforms other classification methods. However, we believe that the results are promising and compatible with the results in literature. For instance, SCA-classification is better than Decision Table and ZeroR methods on the Iris dataset and it has a slightly higher accuracy compared to Decision Trees on Australian dataset. An interesting result is that the method has a similar performance with the Naive Bayes method on the datasets except Haberman where Naive Bayes has a better accuracy. The difference between the performance of the two methods is always less than 5% on the remaining datasets.

Note that a *n*-dimensional CA is needed for a dataset consisting of *n* attributes. Therefore, the number cells in the CA increases exponentially for high dimensional datasets. In section 2.4, it has been noted that a partial CA is utilized in order to overcome this problem. The partial CA consists of only the cells that have a data instance and their neighbors at the beginning. However, as the heat energy propagates in the automaton, new neighbor cells are added to the partial CA. In order to analyze the growth of the CA, three datasets are selected with different number of attributes.

The first dataset is Iris which is a $2-$dimensional dataset. The second one is the Australian dataset with five attributes. The last dataset chosen for the analysis is Breast-wisc which has nine attributes. The increase in the size of CA utilized is given in Figures 5a, 5b and 5c for these three datasets. As seen in the figures, more cells are added to the initial CA throughout the generations. However, the increase in the total number of cells is almost linear for all of the three datasets.

In order to analyze the performance of the proposed method on big data, two additional datasets are generated by *Gaussian Generator* (Handl, 2017). In Table 6, the number of attributes and classes of these two datasets are presented.

The performance comparison of SCA-classification with some other algorithms is presented in Table 8 and Table 7. The other classification algorithms are tested on these datasets by using the machine learning software WEKA(Witten et al., 2016). The success rate obtained by SCA-classification is compatible with the results obtained by other classification methods. However, the runtime performance of SCA-classification is not

Table 4: Experimental results of other algorithms for the datasets are given in the table. References for each dataset are as follows (Gupta, 2015), (Ghazvini et al., 2014),(Gupta, 2015),(Gupta, 2015),(Verma and Mehta, 2014),(Shruti and Khodanpur, 2015),(Parashar et al., 2014),(Shajahaan et al., 2013).

Method	Iris	Banknote	Glass	Heart	Australian	Haberman	Pima	Breast-wisc
Naive Bayes	96.00	88.04	47.66	75.36	85.20	76.47	-	97.42
Decision Tree	-	-	-	-	82.20	-	-	-
C4.5	-	-	-	-	-	-	-	95.57
SVM	-	-	-	-	-	77.12	-	-
Decision Table	92.67	-	68.22	85.07	-	-	-	-
J48	96.00	-	68.69	85.79	-	-	-	-
ID3	-	-	-	-	-	-	-	92.99
Boosting	-	-	-	-	82.20	-	-	-
Bagging	-	-	-	-	84.30	-	-	-
Random Forest	96.00	-	80.37	86.08	84.40	-	-	-
ZeroR	33.33	-	35.51	55.50	-	-	-	-
MLP	96.00	95.81	65.88	85.79	-	-	-	-
GP	96.00	-	66.82	87.10	-	-	-	-
CART	-	-	-	-	-	-	-	92.42
PLS-LDA	-	-	-	-	-	-	74.40	-
FMM	-	-	-	-	-	-	69.28	-
LDA-SVM	-	-	-	-	-	-	75.65	-

Table 5: Analysis of threshold values on iris dataset.

Threshold(°C)	Mean Success(%)	Best solution(%)	Mean Runtime(s)
10	94.67±3.71	100.0	6.01
20	93.33±3.65	100.0	5.68
30	94.00±5.12	100.0	18.53
40	94.33±6.16	100.0	109.47
50	93.33±2.58	96.67	130.42
60	92.00±4.27	100.0	139.79
70	89.33±3.89	93.33	162.02
80	89.00±5.78	96.67	157.51

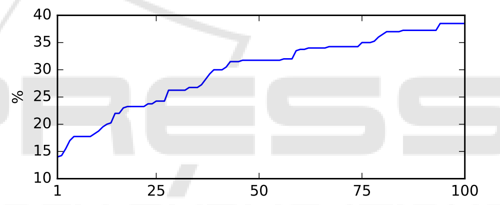
Table 6: The two big Datasets utilized.

Dataset	# of Attributes	# of Classes	# of Instances
Dataset1	3	8	405419
Dataset2	5	8	48046

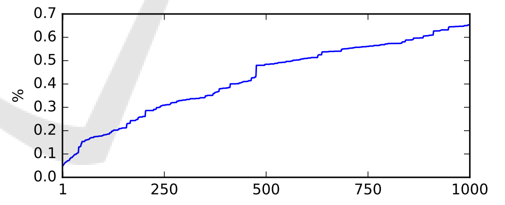
Table 7: Experimental results for Dataset1.

Method	Mean Success(%)	Mean Runtime(s)
SCA-classification	100.0	745.53 ± 9.19
Naive Bayes	100.0	3.20 ± 0.23
MLP	100.0	385.30 ± 5.54
ZeroR	14.61 ± 0.05	0.31 ± 0.35
Decision Table	99.99 ± 0.003	4.99 ± 0.34
Random Forest	100.0	69.58 ± 0.96

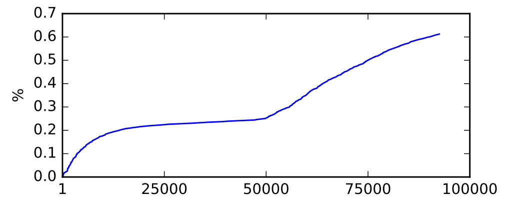
satisfactory compared to the fast classification algorithms like Naive Bayes or Decision Tables. On the first dataset SCA-classification has the lowest runtime performance and on the second one only MultiLayer Perceptrons have a worse performance compared to SCA-classification. However, the method is open to parallelization and as with Multilayer Perceptrons, the runtime efficiency could be improved by parallel execution.



(a) Iris dataset



(b) Australian dataset



(c) Breast-wisc dataset

Figure 5: Relation between the percentage of the cells created in the CA(y-axis) and the number of iterations(x-axis).

4 CONCLUSION

In this paper, a novel approach based on CA is proposed for the classification problem. The method has

Table 8: Experimental results for Dataset2.

Method	Mean Success(%)	Mean Runtime(s)
SCA-classification	47.82 ± 1.52	40.14 ± 2.14
Naive Bayes	39.54 ± 0.47	0.28 ± 0.03
MLP	51.72 ± 1.05	53.21 ± 1.49
ZeroR	14.88 ± 0.19	0.03 ± 0.02
Decision Table	56.33 ± 0.57	3.53 ± 0.18
Random Forest	89.00 ± 0.12	20.50 ± 0.25

an inductive bias inspired from the heat transfer process in nature. The approach provides a framework where cellular automata can be successfully used for the classification process. The approach is tested on datasets with different characteristics and promising results have been obtained. Some future work can be carried out to improve the algorithm. Firstly, the CA utilized have equal number of cells in each dimension. Different number of cells can be chosen in each dimension based on data characteristics. As noted in the previous section, the method is also open to parallelization which would improve the run-time efficiency.

ACKNOWLEDGEMENTS

Enes Burak Dündar contributed this study while he was a student at Yeditepe University.

REFERENCES

Cheeseman, P., Self, M., Kelly, J., Taylor, W., Freeman, D., and Stutz, J. C. (1988). Bayesian classification. In *AAAI*, volume 88, pages 607–611.

Cortes, C. and Vapnik, V. (1995). Support-vector networks. *Machine learning*, 20(3):273–297.

Dündar, E. B. and Korkmaz, E. E. (2018). Data clustering with stochastic cellular automata. *Intelligent Data Analysis*, 22(3).

Ermentrout, G. B. and Edelstein-Keshet, L. (1993). Cellular automata approaches to biological modeling. *Journal of theoretical Biology*, 160(1):97–133.

Esmaeilpour, M., Naderifar, V., and Shukur, Z. (2012). Cellular learning automata approach for data classification. *International Journal of Innovative Computing, Information and Control*, 8(12):8063–8076.

Fawcett, T. (2008). Data mining with cellular automata. *ACM SIGKDD Explorations Newsletter*, 10(1):32–39.

Friedl, M. A. and Brodley, C. E. (1997). Decision tree classification of land cover from remotely sensed data. *Remote sensing of environment*, 61(3):399–409.

Gardner, M. (1970). Mathematical games: The fantastic combinations of john conway's new solitaire game "life". *Scientific American*, 223(4):120–123.

Ghazvini, A., Awwalu, J., and Bakar, A. A. (2014). Comparative analysis of algorithms in supervised classification: A case study of bank notes dataset. *Computer Trends and Technology*, 17(1):39–43.

Gupta, A. (2015). Classification of complex uci datasets using machine learning and evolutionary algorithms. *International journal of scientific and technology research*, 4(5):85–94.

Hall, M. A. and Smith, L. A. (1998). Practical feature subset selection for machine learning.

Handl, J. (2017). Cluster generators. http://personalpages .manchester.ac.uk/mbs/julia.handl/generators.html. Accessed: 2017-12-19.

Hesselbarth, H. and Göbel, I. (1991). Simulation of recrystallization by cellular automata. *Acta Metallurgica et Materialia*, 39(9):2135–2143.

Kokol, P., Povalej, P., Lenic, M., and Stiglic, G. (2004). Building classifier cellular automata. In Sloot, P. M. A., Chopard, B., and Hoekstra, A. G., editors, *ACRI*, volume 3305 of *Lecture Notes in Computer Science*, pages 823–830. Springer.

Langton, C. G. (1984). Self-reproduction in cellular automata. *Physica D: Nonlinear Phenomena*, 10(1):135–144.

Mai, J. and Von Niessen, W. (1992). A cellular automaton model with diffusion for a surface reaction system. *Chemical physics*, 165(1):57–63.

Margolus, N., Toffoli, T., and Vichniac, G. (1986). Cellular-automata supercomputers for fluid-dynamics modeling. *Physical Review Letters*, 56(16):1694.

Newman, C. B. D. and Merz, C. (1998). UCI repository of machine learning databases.

Parashar, A., Burse, K., and Rawat, K. (2014). A comparative approach for pima indians diabetes diagnosis using lda-support vector machine and feed forward neural network. *International Journal of Advanced Research in Computer Science and Software Engineering*, 4:378–383.

Povalej, P., Kokol, P., Družovec, T. W., and Stiglic, B. (2005). Machine-learning with cellular automata. In *International Symposium on Intelligent Data Analysis*, pages 305–315. Springer.

Shajahaan, S. S., Shanthi, S., and ManoChitra, V. (2013). Application of data mining techniques to model breast cancer data. *International Journal of Emerging Technology and Advanced Engineering*, 3(11):362–369.

Shruti, A. and Khodanpur, B. (2015). Comparative study of advanced classification methods. *International Journal on Recent and Innovation Trends in Computing and Communication*, 3(3):1216–1220.

Uzun, A. O., Usta, T., Dündar, E. B., and Korkmaz, E. E. (2018). A solution to the classification problem with cellular automata. *Pattern Recognition Letters*, 116:114 – 120.

Verma, M. and Mehta, D. (2014). A comparative study of techniques in data mining. *International Journal of Emerging Technology and Advanced Engineering*, 4(4):314–321.

Witten, I. H., Frank, E., Hall, M. A., and Pal, C. J. (2016). *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann.