TEST Engineering & Management

January - February 2020
ISSN: 0193 - 4120 Page No. 9116 - 9129

Effective Trust Predictive Model for Online Advertisement Using M-Anfis Classifier

R. Selvavinayagam
Research Scholar, Research and Development Center Bharathiyar University Coimbatore Tamil Nadu India
rsvrrc@gmail.com

Dr. A. Ashok kumar
Assistant Professor Department of Computer Science AlagappaGovt Arts College Karaikudi Tamil Nadu India ashokamjuno@rediffmail.com

Article Info
Volume 82
Page Number: 9116 – 9129
Publication Issue:
January-February 2020

Abstract:
Online advertising (OA) is an effectual way for a business to find new customers, expand its reach, and also to diversify the revenue streams.In real-world, lots of distrusted advertisements are presented; most researchers direct the prediction of trust advertisement, in existing work the prediction accuracy is low. To resolvesuch drawbacks, this paper proposed an effectual trust predictive model for online advertisement using M-ANFIS classifier. This proposed method consists of six steps. Initially, the data are collected from the web. Secondly, those data are preprocessed, the preprocessing phase is split into '3' parts as, replacing of missing attributes, strings to number, and normalization for providing better result in the classification stage. Thirdly, some advertisement related features are extracted. After that, the best features are chosen from the extracted features using Modified Gray Wolf Optimization (MGWO). In the fifth, the advertisement is predicted as trusted and distrusted advertisement centered on the selected feature. Here, the Modified Adaptive Neuro-Fuzzy Inference System (M-ANFIS) is utilized for the purpose of classification. In the sixth, trust value is calculated centered on the click-through rates (CTRs). The proposed classifier's experimental results are contrastedto the existing entropy SVM classifier in respect of statistical measures, for instance, precision, recall, F-score, accuracy, TPR, FPR, and MCC. The proposed trust predictive model for online advertisement provides better accuracy.

Article History
Article Received: *18 May 2019*
Revised: *14 July 2019*
Accepted: *22 December 2019*
Publication: *09 February 2020*

Keywords: *Modified Adaptive Neuro Fuzzy Inference System (M-ANFIS), click through rate (CTR), Modified Gray Wolf Optimization (MGWO), entropy Support vector Machine (SVM)..*

I. INTRODUCTION

The World Wide Web is being extensively utilized for web browsing and it proceeds to grow in advancement towards the semantic web. It has a basic role in all parts of life and its usage is increasing unbelievably [1].

Online display advertising has arisen as the utmost well-known sort of advertising [2, 3]. It is basically practiced in the forms of sponsored search advertisings, con-textual advertisings as well as display advertisings [4].It is basically well-examined subject in academe and also in industry. In OA, online revenue is ascertainedthrough'3'mainaspects: i) average click price (ACP), ii) CTR, iii) number of page views (PVs). Aspects exterior to the advertising system frequently affect the PV, and therefore the

January - February 2020
ISSN: 0193 - 4120 Page No. 9116 - 9129

prime question for advertising is "how to augment revenue with a certain PV" [5].

One vital issue the display advertising endeavors to resolve is to convey the correct ads to the correct populace in the right context promptly. Accurately envisaging the CTR is vital in solving this issue and it has attained maximal research interest in the last years [6, 7].As per the common model of cost-per-click (CPC) for the sponsored search, advertisers are charged just once when the users clicked their ads. In this approach, to augment the income for search engine and uphold a pleasing user experience, search engines need to evaluate the CTR of ads [8]. Most click prediction systems are designed by means of the standard Machine Learning (ML) classification framework [9].

The ads auction's efficiency relies upon the accuracy in addition to calibration of clicking prediction. Hence, the click prediction system requires being robust as well as adaptive and equipped to learn as of massive quantity of data [10].Characteristically, a predictive task is devised as evaluating a function which maps predictor variables to some target. A common solution for constructing predictive models with these predictor variables is to transmute them to a collection of binary features (also known as feature vector) by means of one-hot encoding [11].

A typical system comprises of numerous steps like selection, CTR prediction, relevance filtration, allocation and ranking. The user's input query is initially employed for retrieving a list of candidate ads (i.e. selection). Specially, the selection scheme parses that query and enlarges it to pertinent ad keywords, and after that take the ads as of advertisers' campaigns as per their bidding keywords. Aimed at every chosen ad candidate, the relevance score betwixt ad and query are evaluated, and also, the least pertinent ones are filtered out (relevance filtrations) by the relevance model. The remaining ads are evaluated utilizing the click model for envisaging the click probability (pClick) provided the context information and query (i.e. click prediction) [12].

The paper is ordered as: Section 2 precisely reviews the works associated to the proposed method, sections 3concisely discusses on the proposed methodology, section 4, renders the experiential outcomes and at last, section 5 briefly infers the paper.

I. RELATED WORK

Elizabeth *et.al* [13] examined an effectual personalization paradox approach. This approach utilized experiments that verify whether firms' strategy in gathering information as of social media sites was an imperative factor of how users respond to personalized advertising (online). When firms involve in information compilation, participants reveal a higher CTR for maximal personalized ads, in contrary to their responses. Trusts-building marketing approaches that move trust as of signal trust or another website with information cues could cancel out the negative effects.

Marco *et.al* [14] modeled a fictional webpage that performed as the experiential stimulus. Particularly, this framework influenced the source credibility and news truthfulness by monitoring the changes in person's responses whilst distinguishing betwixt the monitored credibility and objective trustfulness of the particular news. As of a managerial perspective, the outcomes could partially re-assure the brand managers that the brand ads would not suffer as of emerging next to false news as the source was believable.

Sangmee*et.al* [15] paid attention to location-centered advertising in mobile gadgets by examining the psychological impacts of locational congruity (LC), product involvement (PI) and

January - February 2020
ISSN: 0193 - 4120 Page No. 9116 - 9129

information tailoring (IT) on consumer attitudes. A two-sorts of IT: customization vs. personalization, two-level of IC: low vs. high and 2 levels of PI: high vs. low betwixt-subjects experiments were made for examining research question and analyzing this approach.

Weiyu*et.al* [16] proffered a trust prediction (TP) framework that integrates co-clustering methodology with the multiple modal similarity metrics for TP on social-rating networks. This framework initially co-clusters both items and users into several sub-groups to ascertain potential users-item interest sub-groups flooded in the huge user-item matrices. Subsequently, in every sub-group, the implicit and even explicit similarities betwixt '2' users were evaluated. The experiential outcomes elucidated the framework's effectiveness and the co-clustering methodology's role for TP.

Brian *et.al* [17] proffered an integration of strategies, employed by an OA firm Dstillery, to learn many designs as of eminently high-dimension data effectually and with no human interventions. This combination encompasses, a novel updating rule for certain processes and simpler-yet-effectual transfer learning. This work offered a sophisticated methodology that could elevate the benefits as of inductive transfers.

Perlich*et.al* [18] introduced a clear problem formulation integrated with a big-scale production ML system for the aimed display advertising. This strategy offered the model of the transfer learning scheme. And, it proffered the clear experiential evaluation, evincing that the disparate transfer stages indeed every added value. It also rendered production outcomes across advertising clients as of disparate industries, elucidating the system performance.

Hongxia*et.al* [19] propounded a bipartite graph depiction for tackling the CVRs prediction issue in a computational ad for effectual user-ranking and recommendations for campaigns. Primarily, the*AdvUserGraph* (graph) depiction of user attitudes (historical) and also the action significance given on these graphs were introduced; then proffered the propounded ADNI algorithm for determining the competently interested users centered on a specified advertiser drive.

Wendi *et.al* [20] propounded a PMTA (Probabilistic Multi-Touch Attributions) design which regarded the ads which have been clicked or seen by a user and also when every such interaction transpired. The PMTA was fitted to the perceived data (conversion rate and delay) instead of depending on simplistic presumptions. This PMTA was assessed on a huge existent data set. The experiments have corroborated their higher effectiveness in both attribution analysis and conversion prediction contrasted to the prevailing attribution designs. This approach utilized only a few data sets for examining the outcomes.

II. PROPOSED METHODOLOGY

This paper proposed an effective trust predictive model for an online advertisement based on CTR. This proposed method comprisessix steps such as (a) dataset collection, (b) Preprocessing, (c) Feature extraction, (d) Feature selection (FS), (e) Classification, and (f) trust calculation. Initially, the dataset is collected as of online. Secondly, the data taken as of the dataset is preprocessed using 'replacing of missing attributes' for predicting the better result, 'strings to number' to replace strings as numbers, and lastly, the data is to be normalized. Thirdly, some advertisement features are extorted. In the fourth stage, the extorted features are chosen using MGWO. In the fifth phase, perform classification operation for predicting trust advertisement using the modified neuro-fuzzy system. In the sixth stage, find trust calculation using the specified equation. At last, the performance shown by the proposed system is estimated and contrasted to the existent methods. The proposed system could be delineated in detail utilizing the block diagramexhibited in fig.1

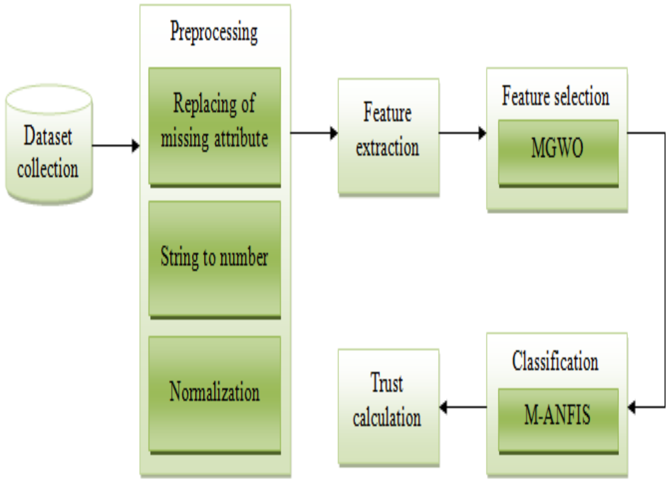


Figure 1: Block diagram for the proposed trust predictive model for the online advertisement

3.1 Dataset Collection

This proposed method uses a real-world CTR prediction dataset available on Kaggle, which is the largest and most diverse data communities in the globe and KDD CUP, which is extensivelyutilized as the few publicly obtainable datasets.

3.2 Preprocessing

Data pre-processing delineates any sort of processing carried out on raw data for preparingthem for a different processing process. This proposed method uses '3' steps for instance, (a) replacing of missing attributes, (b) strings to number, and (c) Normalization which are delineated below as,

3.2.1 Replacing of Missing Attributes

Here, the missing attributes are replaced. In the dataset, there is a big possibility of data being missed andthese data are replaced by a maximum number of features occurrences which is expressed in below equation (1).

$$M_A = Max(F_i) \tag{1}$$

Where, M_A denotes the missing attribute, F_i denotes the feature sets.

3.2.2 Strings to Number

In this step, strings are changed as the numbers. The strings are manually changed as the number value, for example, "a" is the string which is changed as "1". Similarly, for all alphabetic letters, the number is assigned.

3.2.3 Normalization

It scales the attribute data to perfectly fit into a particular range. Amongst different normalization, Min-Max Normalization would be more useful. This sort of Normalization transmutes a value D to N that fitsin [0, 1]. It is signified by the equ (2) below

$$N = \left(\left(\frac{(D - D_{Min})}{(D_{Mac} - D_{\min})} \right) * (1 - 0) + 0 \right) \tag{2}$$

Where, N signifies the normalization, zero and one denotes the range.

3.3 Feature Extraction

The features are extorted. It diminishes the resources that are required to signify a particular dataset. The advertisement features, site features, device features and app features are extorted from the dataset. This is mathematically represented as,

$$F_i = \{F_1, F_2, F_3, ...F_N\} \tag{3}$$

Where, N represents the number of features, and F_i denotes the feature set.

January - February 2020
ISSN: 0193 - 4120 Page No. 9116 - 9129

3.4 Feature Selection

In this phase, the extorted features are chosen using MGWOalgorithm. This is asignificant part of machine learning. FSalludes to the process of lessening the inputs for processing analysis or finding the most vital inputs. The MGWO for FS is explained in the below section.

3.4.1 Modified Gray Wolf Optimization (MGWO)

Grey wolf optimization is a swarm intelligent method that imitates the leadership hierarchy of wolves, which isfamous for its group hunting. The whole group livesin the form of a pack. It mightencompass the utmost rigorous leading hierarchy, where Malesalong with females are regarded as the pack leaders. This pack has alpha(α), delta(δ), beta(β), along withomega (ω). Contingent on the GWO design, the fitness solutionscould be determined as α followed by 2nd and3rd better solution β and δ, respectively. Furthermore, the remaining candidate solutions are alluded to as ω. Its hunting phases are,

a. Encircling,
b. Crossover Mutation,
c. Hunting and,
d. Attacking the preys

3.4.1.1 Encircling Prey

The encircling plan around the prey is mathematically modeled by means of proposing the subsequent equations as,

$$\vec{D} = \left| \vec{C} . \vec{E}_p(t) - \vec{E}(t) \right| \tag{4}$$

$$\vec{E}(t+1) = \vec{E}_p(t) - \vec{A} . \vec{D} \tag{5}$$

$$\vec{A} = 2\vec{a}.rand_1 - \vec{a} \tag{6}$$

$$\vec{C} = 2.rand_2 \tag{7}$$

Where, $\vec{E}(t+1)$ is the wolf's position at $(t+1)^{th}$ iteration, $\vec{D}$ signifies a difference vector providedin eq. (4), $\vec{E}(t)$implies the wolf's position at t^{th} iteration, $\vec{A}$ and $\vec{C}$ are co-efficient vectors, $\vec{E}_p(t)$ signifies the prey's position at t^{th} iteration and $\vec{a}$ implies a linearly decreasing vector as of 2 to 0 over iterations, written as

$$\vec{a} = 2 - 2 . \left(\frac{t}{Maximum\ no.of\ \ iterations} \right) \tag{8}$$

And, $rand_1, rand_2$ indicates the uniformly distributed random vectors and its component lie within 0 to 1.

3.4.1.2 Crossover Mutation

Determine the best(E_α), the 2nd best (E_β) and the 3rd best (E_δ) hunt agents utilizing crossover and mutation operation. These operations make optimization utmost effective. For *n* parents, *n* – 1 displacement points are picked and the genes betwixtsuch points are selected, which leads to the development of offspring chromosomes. This is performedutilizing the crossover points which areexhibited in fig 2.

January - February 2020
ISSN: 0193 - 4120 Page No. 9116 - 9129

a	b	c	d	e	f	g	h	i	j	Current position
0	1	2	3	4	5	6	7	8	9	Best personal experience
A	B	C	D	E	F	G	H	I	J	Best global position among all wolves

a	b	c	3	4	5	6	H	I	J	Offspring 1
A	B	C	d	e	f	g	7	8	9	Offspring 2
0	1	2	D	E	F	G	h	i	j	Offspring 3

Figure 2: Crossover

After crossover, the mutation operator is employed to solutions (wolves). This operator picks a gene as of a wolf arbitrarilyas well asalters its content. From the fig. 3, it can be stated that the mutation operator is implemented to the fifth gene and alsoalters its value to 1.

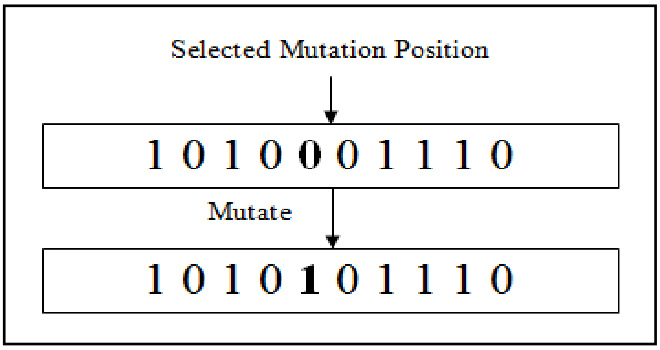


Figure 3: A solution before and after mutation

3.4.1.3 Hunting

The grey wolves' hunting strategycould be mathematically modeled by means of approximating the prey position with the aid of α, β and δ solutions (wolves). After mutation, re-new the current hunt agent's location using below eq(12).

$$\vec{E}_1 = \vec{E}_\alpha - \vec{A}_\alpha - \vec{D}_\alpha \tag{9}$$

$$\vec{E}_2 = \vec{E}_\beta - \vec{E}_\beta - \vec{D}_\beta \tag{10}$$

$$\vec{E}_3 = \vec{E}_\delta - \vec{A}_\delta - \vec{D}_\delta \tag{11}$$

$$\vec{E}(t+1) = \frac{\vec{E}_1 + \vec{E}_2 + \vec{E}_3}{3} \tag{12}$$

The fitness value for all hunts are evaluated and the E_α, E_β and E_δ values are updated.

3.4.1.4 Attacking Prey

It is clear that when the prey stops moving, the wolf will slay the prey and like this, they finish their hunting process by repeating the encircling, hunting and crossover mutation, which are delineated above. The MGWO's pseudo code is evinced in fig. 4

```
Begin
    Initialize the Grey wolf population
    Initialize parameters
    Calculate the fitness of each search agents using objective function
    Evaluate the fitness of each wolf
    Select E_α =Best hunt agent
           E_β =Second best hunt agent
           E_δ =Third best hunt agent
    Update the position of using crossover and mutation as defined in
    section 3.4.1.2
    While (iter < Iter_max )
        For each hunt agents
            Update the position of the each current hunt agent by eq. (12)
        End for
        Update E_α , E_β and E_δ
        Iter=iter+1
    End while
End
```

Figure 4: Pseudo code for MGWO

January - February 2020
ISSN: 0193 - 4120 Page No. 9116 - 9129

3.5 Classification utilizing Modified ANFIS system

In this phase, the selected features are analyzed using M-ANFIS to check the trust advertisement. In the proposed work, M-ANFIS combines K-Medoid algorithm and ANFIS for the prediction of trust in the advertisement. At first, clustering is performed utilizing K-Medoid clustering algorithm and then classification is performed utilizing ANFIS, which in combination, said as M-ANFIS.

3.5.1 K-Medoid Clustering Algorithm

Arbitrarily select k data items as primary medics for representing the k clusters. The remaining items are in corporate in a cluster that contains its medoid nearest to them. Afterward, a new medoid which could signify the cluster better is ascertained. Rest of the data items are once moreallotted to the clusters encompassing nearest medoid. In iterations, the medoids alter their locations. The technique lessens the total of the dissimilarities betwixtevery data item and its equivalent medoids. Also, this cycle is recurring until no medoid alters its place. This is the end of this processand the resultinglast clusters with their respective medoids are attained. K Clusters are generated that are reliant upon the medoids and every single data members are kept in the pertinent cluster grounded on adjacent medoid. Thisalgorithm is exhibited below.

Step 1: Let $C = \{C_1, C_{2,} ..., C_j, ..., C_8\}$ be the set of cluster heads (CH).

Step 2: Allocate each cluster nodes (CNs) to the adjacentCH to obtain the clusters. Then, using the Euclidean distance (ED) formula, the distance of the CH from other CNs is determined as inequ (13).

$$D = \sqrt{(m_1 - n_1)^2 + (m_2 - n_2)^2} \tag{13}$$

Here (m_1, n_1) and (m_2, n_2) indicates the co-ordinates of aCH and the CNs. Compute the total of distances for all CNs to aCH.

Step 3: Arbitrarilypick a CN'C_{random}'to replace CH node C_j, with the condition that the residual energy of C_{random} should be higher on considering the average residual energy of all CNs.

Step 4: Allot the CNs to the closest new CH and obtain the clustering outcome. Subsequently, evaluate the ED of aCH as well as the other CNs utilizing the equation (13). And calculate the total of distances for all CNs to the CH.

Step 5: If the total of distances equals the formertotal of distances value, then this algorithm is terminated, else, Step 3 is re-executed.

3.5.2 M-ANFIS

A fuzzy model termed ANFIS is in an adaptive structure for stimulating adaptation and also learning. On account of this structure, the ANFIS-type modeling became more systematic. The M-ANFIS embraces '5' layers in it. The attained clustered features are inputted to the 1st layer of the M-ANFIS. In its 5 layers, the 4th and 1st contains adaptive nodes, whereas, the 3rd, 2nd, and 5th layers comprise fixed nodes. The images could be accurately classified utilizing M-ANFIS. M-ANFIS has '2' fundamental rules as signifiedbelow,

Rule I: If d is R_i as well as g is S_i then,

$$k_i = d_i F_i + g_i F_{i+1} + l_i \tag{14}$$

Rule II: If d is R_{i+1} and g is S_{i+1} then,

$$k_{i+1} = d_{i+1} F_i + g_{i+1} F_{i+1} + l_{i+1} \tag{15}$$

Here

R_i, S_i, R_{i+1} and S_{i+1} - fuzzy sets

F_i and F_{i+1} – The "extracted features" in the proposed system.

$d_i, g_i, l_i, d_{i+1}, g_{i+1}$ and l_{i+1} - parameter set.

The ANFIS structure could be elucidated using Figure 5,

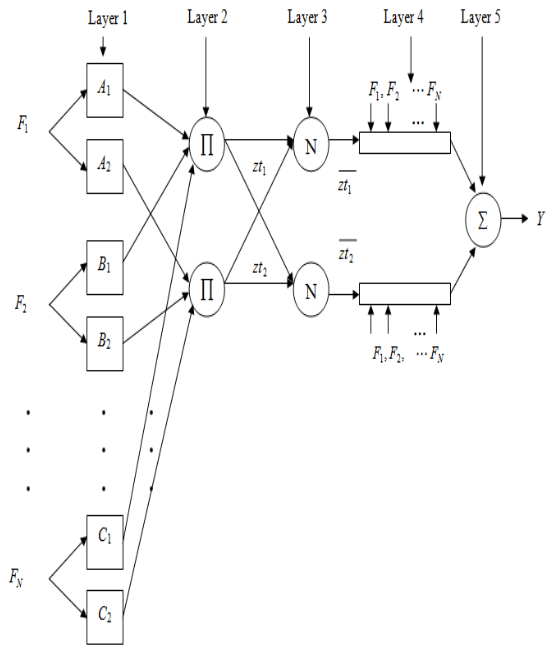


Figure 5: General Structure of ANFIS

As afore-mentioned, the M-ANFIS classifier comprises 5 layers, they are,

Layer-1: Its nodes adapted to a function parameter and their (nodes) output is regarded as a degree of membership value which is attained from the membership function (MF). A bell MF is utilized in the proposed work. It is proffered as,

$$\mu_{Ri}(F_i) = \frac{1}{1 + \left(F_1 - {c_i}/{a_i} \right)^{2b_i}} \tag{16}$$

Here,

a_i, c_i and b_i - Parameters of MFs (or premise parameters) that could alter the MF's shape.

Layer 2: Its nodesare fixednodes. Its circle node is specified as X .Their output node is the outcome of multiplication of the incoming values into a node and transmitted value to the subsequent node. Every single node signifies the firing strength (FS) for rules.

$$G_{2,i} = Zt_i = \mu_{Ri}(F_i) \times \mu_{Ri}(F_{i+1}) \tag{17}$$

Where

Zt_i - Output, that is the FS of every rule.

Layer-3: It has fixed nodes and its circle node is symbolized as Y . Every single node has a function that is to evaluate the ratio betwixt the i^{th} rules FS and the total of all the rules' FSs. The attained outcome is regarded as the normalizing FS. Its formulation isproffered as,

$$\mathrm{G}_{3,\mathrm{i}} = \overline{\mathrm{Zt}}_\mathrm{i} = \frac{\mathrm{Zt}_\mathrm{i}}{\mathrm{Zt}_\mathrm{i}}, \quad \mathrm{i} = 1,2,3,\ldots,6 \tag{18}$$

Layer-4: Its each node is the adaptive node to the output. Its node function is proffered as:

$$G_{4,i} = \overline{Zt}_i \, . \, k_i \tag{19}$$

Here,

$\overline{Zt}_i$ - Normalized FS as of the 3rd layer

k_i - Rule of this system.

Layer-5: It has a single fixed node. This node evaluates the output by summating the whole incoming signals as of the former node. Its circle node is symbolized as $\sum$:

$$G_{5,i} = \sum_i \overline{Zt}_i k_i \tag{20}$$

Lastly, the M-ANFIS classifies the trusted advertisement and distrusted advertisement.

3.6 Trust Calculation

After predicting the trusted advertisement, the trust is evaluated centered on CTR, site domain and app domain. CTR gauges the number of clicks advertisers get on their ads per impression. In this trust calculation, the total clicks are considered. It is evaluated as,

$$T_c = Max\left(\frac{1}{\sum(S_d + A_d)} * C\right) \tag{21}$$

Where,

T_c - trust calculation,

S_d - Site domain,

A_d - App domain

C - ad clicks

III. RESULT AND DISCUSSION

The proposed trust predictive model for online advertisement which is centered on CLR is employed in the working platform of JAVA. The experiential outcomes were attained and examined centered on certain statistic measures like precision, F-Score, recall, accuracy, false-positive rates (FPR), true positive rates (TPR), Mathew's Correlation Coefficient (MCC), fitness function and computation time. These measures were evaluated and contrasted to the prevailing entropy SVM methodology.

4.1 Comparative analysis

Here, the performance proffered by the proposed M-ANFIS and the prevailing Entropy SVM is examined centered on the statistical measures. Moreover, the statistical measure values of the proposed and existing approaches could be elucidated using table-1.

Table 1: Illustrate the performance of the proposed system with the existing system in terms of statistical measures

(a)

Number of Data	PROPOSED M-ANFIS				EXISTING Entropy SVM			
	Precision	Recall	F-Score	Accuracy	Precision	Recall	F-Score	Accuracy
100	84.74	83.33	84.03	81	82.43	80.45	82.89	80.32
200	98.03	83.33	90.09	83.5	96.67	80.67	78.23	72.82
300	97.27	94.33	95.78	92.66	93.53	91.34	93.34	91.12
400	97.22	95.89	96.55	93.75	94.56	92.43	94.34	92.15
500	97.40	96.77	97.08	94.6	95.45	93.45	85.34	80.12

(b)

Number of Data	PROPOSED M-ANFIS				EXISTING Entropy SVM			
	TPR	FPR	MCC	CT	TPR	FPR	MCC	CT
100	0.8333	0.225	0.6059	18	0.7743	0.3134	0.4832	25
200	0.8333	0.15	0.4834	42	0.7843	0.1934	0.4354	53
300	0.9434	0.2	0.6810	67	0.9093	0.254	0.6345	76
400	0.9589	0.2857	0.6340	97	0.9134	0.3145	0.5899	103
500	0.9677	0.3428	0.6016	122	0.9234	0.3856	0.5663	129

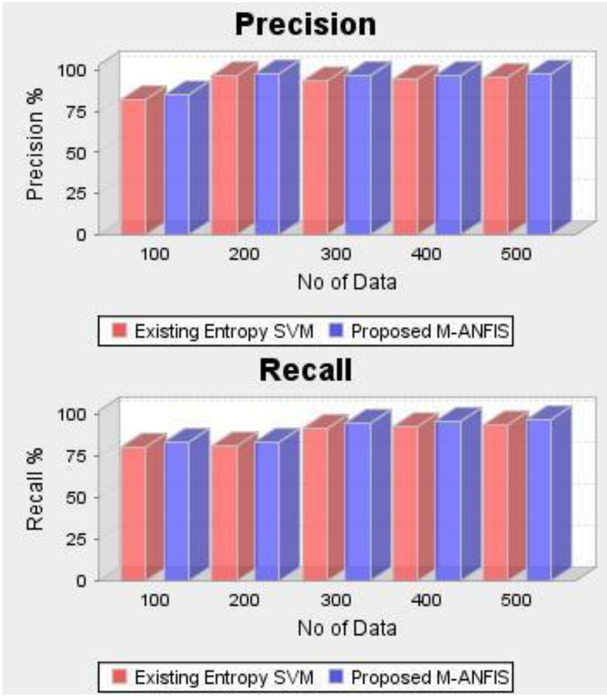
Discussion: Table-1 (a) contrasted the performance shown by the proposed M-ANFIS system with the existent Entropy SVM system in respect of precision, F-Score, recall, and accuracy.

January - February 2020
ISSN: 0193 - 4120 Page No. 9116 - 9129

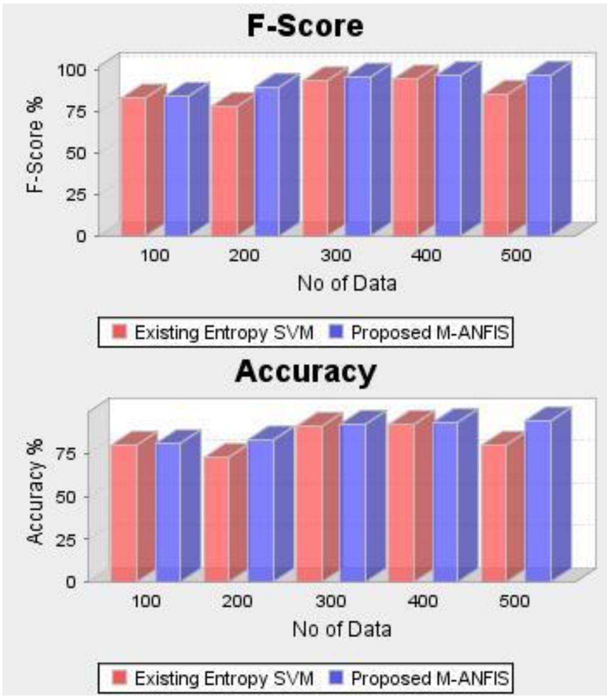
Table.1 (b) also evinces the performance proffered by those systems in respect of TPR, FPR, MCC, and CT. Performance proffered by the systems varies centered on the total data. The proposed M-ANFIS has 97.40-accuracy for 500 data which is high when contrasted to the existent entropy SVM classification scheme. Similarly, for the remaining 200 to 500 data, the proposed M-ANFIS attained high accuracy. The proposed M-ANFIS has 84.74 precision for 100 data, but the existent system proffered 82.43 precision. Consequently, it is inferred that the proposed M-ANFIS proffered better performance when contrasted to the existent entropy SVM classification approach.

4.1.1 Precision, Recall, F-Score and Accuracy

Here, the system performance is explained centered on precision, F-Measure, accuracy, and recall. For computing precision, the number of accurate positive predictions is divided with the total positive predictions, where the derived outcome of the existent system and proposed system could well be elucidated using figure 6 (a). For computing Recall, the number of positive predictions is divided with the total positives, where the recall performance is evinced in fig.6 (b). F-Score gauges the classification model's accuracy relying on the recall together with the precision metrics, where the graphical depiction of F-Score value is evinced in figure 6 (c). Generally, accuracy relies on the way wherein the data are collected. It is judged by contrasting several measurements as of diverse or same sources. The accuracy performance shown by the proposed M-ANFIS and the existing entropy SVM is evinced in fig 6 (d).



(a) (b)



(d) (e)

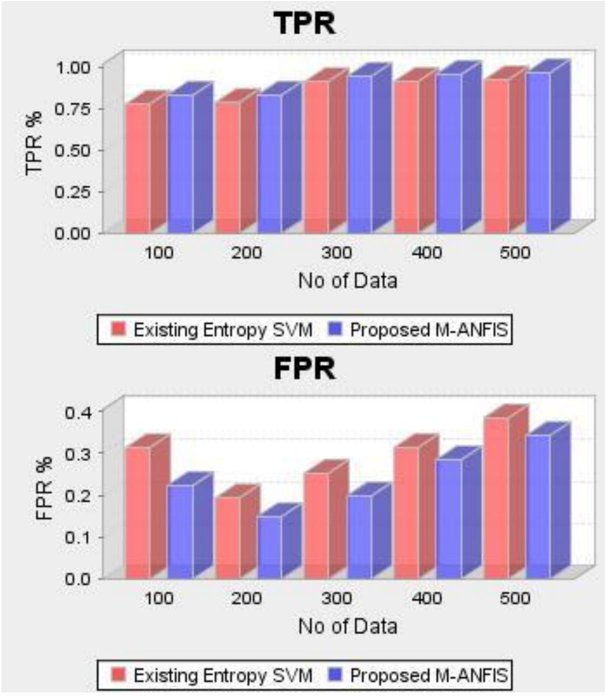
Figure 6: Graph shows the performance of the proposed classifier with the existing classifier in terms of precision, recall, F-Score, and accuracy

January - February 2020
ISSN: 0193 - 4120 Page No. 9116 - 9129

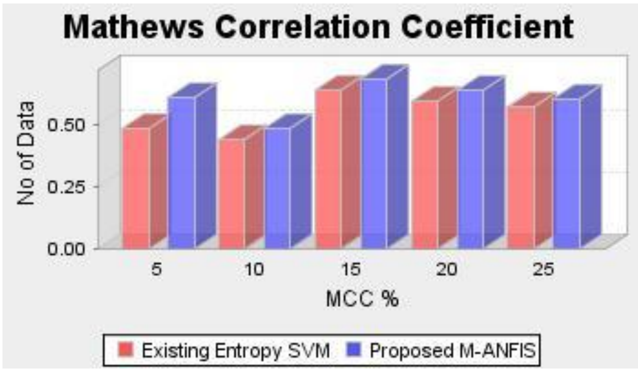
Discussion: From fig.6, the proposed M-ANFIS has shown better results. For 100 data, the precision values are 84.74 and 82.43 respectively for M-ANFIS and Entropy SVM. Similarly, for the remaining 200 to 500 data, the precision performance showed by the proposed and existing systems vary. Also, For 400 data, the recall values are 95.89 and 92.43 for M-ANFIS and Entropy SVM. Then for 300 data, the F-Score values are 95.78 and 93.34 respectively for proposed and existing classifiers. Regarding accuracy, for 200 data, the accuracy values are 83.5 and 72.82 for M-ANFIS and Entropy SVM classifiers. The above interpretations were identical for all data. Consequently, it is inferred that the proposed M-ANFIS classifier proffered better performance as contrasted to the existent entropy SVM classifier.

4.1.2 TPR, FPR, MCC

TPR is a statistical gauge of performance. It is utilized to assess the efficiency of the classification system. The TPR evaluation result of the systems is evinced in fig 7 (a). FPR indicates the probability of false rejections of the null hypothesis for test data. The FPR is evaluated as the ratio betwixt the number of negatives incorrectly categorized as positives and the total actual negatives, where the FPR evaluation result of the systems is evinced in fig 7 (b). MCC is employed as a quality of measure in binary classifications. A binary classification comprises '2' classes. This measure regarded the false and also true positives. It is characterized as a balanced measure that could be deployed even on the off-chance that the classes are of varied sizes. MCC results of the existing entropy SVM and proposed M-ANFIS is evinced in fig 7 (c).



(a) (b)



(c)

Figure 7: Graph exhibits the performance of the M-ANFIS with the Entropy SVM based on TPR, FPR, and MCC.

Discussion: From fig 7, for 100 data, the TPR values are 0.833 and 0.7743 respectively for proposed M-ANFIS and existing entropy SVM. For 200 data, the TPR values are 0.8333 and 0.7843 for the M-ANFIS classifier and entropy SVM classifier, which corroborates that the TPR value of the proposed system is high when contrasted to the existing entropy SVM classifier. For 400 data, the FPR values are 0.2857 and 0.3145 for M-ANFIS and entropy SVM classifier.

TEST Engineering & Management
January - February 2020
ISSN: 0193 - 4120 Page No. 9116 - 9129

Grounded on MCC measure, for 500 data, the proposed M-ANFIS has 0.6016 MCC, and the existing system has 0.5663 MCC. From this description, it is inferred that the proposed M-ANFIS classifier system attained better performance when contrasted to the existing system.

4.1.3 Iteration Vs Fitness

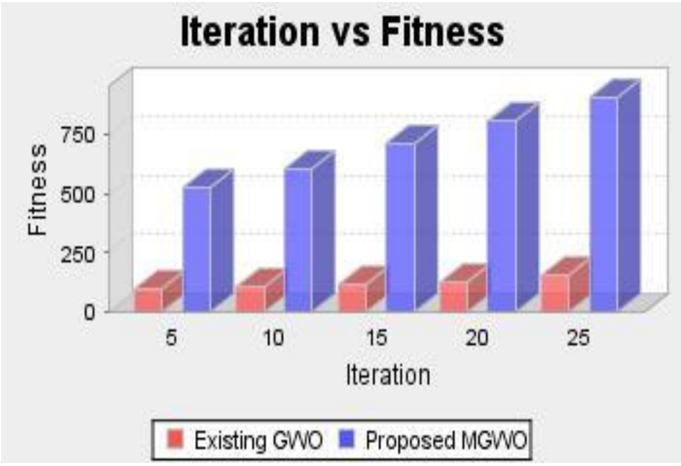


Figure 8: Demonstrate the convergence value of the proposed MGWO with the existing GWO.

Discussion: The convergence of the existing GWO optimization algorithm is contrasted to the proposed MGWO as evinced in Fig 8. The fitness performance varies centered on the iterations ranging as of 5 to 25. From fig 8, the proposed MGWO achieves a better result when contrasted with the existent GWO.

4.1.4 Computational Time

It is the period of time taken to execute a computational process. The computation time of the existing entropy SVM is contrasted to the proposed M-ANFIS and is elucidated using fig 9.

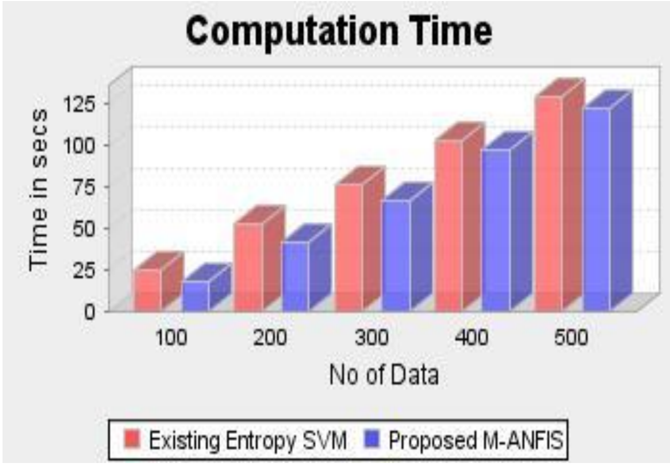


Figure 9: Computational time of the proposed classifier with the existing classifier.

Discussion: The computation time taken by the proposed M-ANFIS and the existent Entropy SVM classifiers are contrasted in Fig.9. This computation time varies centered on the total data present in the system. For 100 data, the proposed classifier consumed 18s but the existent classifier consumed 25s which is taking high time when contrasted to the proposed system. Similarly, for the remaining 200 to 500 data, the proposed M-ANFIS takes lesser time contrasted to the existing Entropy SVM classifier. Consequently, the proposed M-ANFIS exhibited pre-eminent performance.

IV. CONCLUSION

An effectual trust predictive model was proposed for online advertisement utilizing M-ANFIS. Performances shown by the proposed TP of online advertisement have been examined utilizing the CTR prediction data set existing in kaggle. After predicting the trust advertisements, its trust value is determined. In the TP model, the proposed M-ANFIS classifier accurately classified the distrust and trust advertisements as of the provided data. The comparison outcomes illustrated the trust predictive model of the proposed system utilizing the M-ANFIS classifier. It has achieved high precision, F-Measure, accuracy, and recall. And, the proposed classifier

January - February 2020
ISSN: 0193 - 4120 Page No. 9116 - 9129

took less time for testing the data. Regarding fitness measure, the proposed MGWO attained better fitness value contrasting to the existent GWO optimization algorithm in the feature selection process. Consequently, the proposed trust predictive model for online advertisement utilizing the M-ANFIS system has accurately predicted the distrust and trust advertisements and it gives better trust value.

V. REFERENCES

1. Shanmuga Priya, S. and S. Padmavathi, "Comparative analysis of classification algorithms for predicting the advertisements on webpages", Asian Journal of Information Technology, Vol. 15, No. 4, pp. 738-742, 2016.
2. Malarvizhi R, Anbu Thiruvarangan K, and Srinivasan A, "Advertising viewability prediction on the web", International Journal of Pure and Applied Mathematics, Vol. 119, No. 14, pp. 1295-1305, 2018
3. Chong Wang, Achir Kalra, Cristian Borcea, and Yi Chen, "Viewability prediction for online display ads", In Proceedings of the 24th ACM International on Conference on Information and Knowledge Management, pp. 413-422. ACM, 2015.
4. Deepak Agarwal, Bo Long, Jonathan Traupman, Doris Xin, and Liang Zhang, "Laser: A scalable response prediction platform for online advertising", In Proceedings of the 7th ACM international conference on Web search and data mining, pp. 173-182. ACM, 2014.
5. Yuhan Su, Zhongming Jin, Ying Chen, Xinghai Sun, Yaming Yang, Fangzheng Qiao, Fen Xia, and Wei Xu, "Improving click-through rate prediction accuracy in online advertising by transfer learning", In Proceedings of the International Conference on Web Intelligence, pp. 1018-1025. ACM, 2017.
6. Olivier Chapelle, Eren Manavoglu, and Romer Rosales, "Simple and scalable response prediction for display advertising", ACM Transactions on Intelligent Systems and Technology (TIST), Vol. 5, No. 4, pp. 61, 2015.
7. Brendan McMahan, H., Gary Holt, David Sculley, Michael Young, Dietmar Ebner, Julian Grady, Lan Nie et al, "Ad click prediction: a view from the trenches", In Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1222-1230. ACM, 2013.
8. Yuyu Zhang, Hanjun Dai, Chang Xu, Jun Feng, Taifeng Wang, Jiang Bian, Bin Wang, and Tie-Yan Liu, "Sequential click prediction for sponsored search with recurrent neural networks", In AAAI, Vol. 14, PP. 1369-1375, 2014.
9. Rishabh Iyer, Nimit Acharya, Tanuja Bompada, Denis Charles, and Eren Manavoglu, "A unified batch online learning framework for click prediction", 2018.
10. Xinran He, Junfeng Pan, Ou Jin, Tianbing Xu, Bo Liu, Tao Xu, Yanxin Shi et al, "Practical lessons from predicting clicks on ads at facebook", In Proceedings of the Eighth International Workshop on Data Mining for Online Advertising, pp. 1-9. ACM, 2014.
11. Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua, "Neural collaborative filtering", In Proceedings of the 26th International Conference on World Wide Web, pp. 173-182. International World Wide Web Conferences Steering Committee, 2017.
12. Xiaoliang Ling, Weiwei Deng, Chen Gu, Hucheng Zhou, Cui Li, and Feng Sun, "Model ensemble for click prediction in bing search ads", In Proceedings of the 26th International Conference on World Wide Web Companion, pp. 689-698. International World Wide Web Conferences Steering Committee, 2017.
13. Elizabeth Aguirre, Dominik Mahr, Dhruv Grewal, Ko de Ruyter, and Martin Wetzels, "Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness", Journal of Retailing, Vol. 91, No. 1, pp. 34-49, 2015.
14. Marco Visentin, Gabriele Pizzi, and Marco Pichierri, "Fake news, real problems for brands: the impact of content truthfulness and source credibility on consumers' behavioral intentions toward the advertised brands", Journal of Interactive Marketing, Vol. 45, pp. 99-112, 2019.
15. Sangmee Lee, Ki Joon Kim, and S. Shyam Sundar, "Customization in location-based advertising: Effects of tailoring source, locational congruity, and product involvement on ad attitudes", Computers in Human Behavior, Vol. 51, pp. 336-343, 2015.

January - February 2020
ISSN: 0193 - 4120 Page No. 9116 - 9129

16. Weiyu Zhang, Bin Wu, and Yang Liu, "Cluster-level trust prediction based on multi-modal social networks", Neurocomputing, Vol. 210, pp. 206-216, 2016.
17. Brian Dalessandro, Daizhuo Chen, Troy Raeder, Claudia Perlich, Melinda Han Williams, and Foster Provost, "Scalable hands-free transfer learning for online advertising", In Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 1573-1582. ACM, 2014.
18. Claudia Perlich, Brian Dalessandro, Troy Raeder, Ori Stitelman, and Foster Provost, "Machine learning for targeted display advertising: Transfer learning in action", Machine Learning, Vol. 95, No. 1, pp. 103-127, 2014.
19. Hongxia Yang, Yada Zhu, and Jingrui He, "Local algorithm for user action prediction towards display ads", In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 2091-2099. ACM, 2017.
20. Wendi Ji, Xiaoling Wang, and Dell Zhang, "A probabilistic multi-touch attribution model for online advertising", In Proceedings of the 25th ACM International on Conference on Information and Knowledge Management, pp. 1373-1382. ACM, 2016.