Deep Maximum Entropy with Memetic Reinforced Learning for Agriculture Drought Prediction

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Abstract:
The most obvious impact of agricultural drought is a decrease in crop yield as a result of irregular and inadequate rainfall. Drought forecasting has a massive effect on vegetation. As a result, predicting the occurrence of drought early in the season could help to mitigate the detrimental effects of drought. Drought prediction requires information on rainfall, temperature, and pressure for its decision-making model in order to enact proper agriculture planning. Though there is much literature related to agriculture drought prediction, the class imbalance is the most influential factor which affects the learning rate of the classification model. This paper focuses on overcoming class imbalance to optimize agriculture drought prediction model by devising a deep learning and memetic nature inspired model. In this proposed model, deep maximum entropy is used for identifying decision features in the dataset that provides maximum information about the conditional feature to improve the accuracy of drought prediction. In conventional RL, a policy that gets high reward alone is considered for training the model randomly. Deep Maximum Entropy Reinforcement Learning aims to maximize entropy of policy to handle the class imbalance issue. The parameters of the RL are optimized by inducing shuffled frog leaping algorithms with its food searching strategy for assigning optimal values to the parameters of the RL involved in prediction of Agriculture Drought. The simulation results proved that the proposed DME-MRL produces the highest rate of accuracy for agriculture drought prediction compared to other existing models. 3304

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1. Introduction

India is the world's second-largest producer of agricultural crop production. It plays a key part in India's socio-economic conditions because it is the broadest economic sector based on its demographics features [1]. Many factors, such as economy and climate have an impact on crop productivity. The temperature, weeds, Cultivation, irrigation, soil, pesticides and harvesting are other pertinent aspects of factors that affect agriculture [2]. Hence it is necessary for the companies to keep track of previous crop field data, which will aid supply chain operations for their commercial transactions. As a result of the massive rise in industries, global warming seems to have a significant impact on India's climatic conditions, that has a significant impact on agriculture. Drought prediction is a serious repute to initial cautionary for drought managements among various challenges associated to effective crop growth maximization [3]. The most obvious impact of agriculture drought would be a decrease in crop yield as a result of irregular and insufficient rainfall. Every year, most of regions are threatened by drought, which has a serious influence on farmers. As a result, forecasting drought occurrence early in the season could help to mitigate the harmful effects of drought. To execute smart farming, drought prediction requires data on rainfall, temperature, and pressure for its decision-making model to boost crop growth by better utilizing available resources whilst minimizing environmental impact.

Drought is a really scary situation that undermines the socio-economic situation. Its prevalence and ferocity greatly depend on location. Most of the countries confront challenge in determining the policies and techniques for mitigating the risk of drought [4]. This demands the necessity of collecting hidden information on drought features, such as intensity, spatial pattern, and periodicity, which is essential for decision-making. It's critical to figure out the relationship between various climatic factors and identify the discerning traits which may be employed to anticipate the occurrence of drought using a large amount of historical data.

It is necessary to have an efficient framework which extracts relevant knowledge from large amounts and reveals valuable and pertinent information for drought risk management. In recent decades, data mining has been an essential approach for discovering hidden patterns and relationships across features in a massive dataset. It's a multifunctional approach that can allow you to make better decisions, reduce cost, and speed up the processing time of products to reach the market. But uncertainty and class imbalance are the major issues while using conventional mining approaches such as clustering or classification which results in poor prediction accuracy and overfitting problem.

Hence, in this paper to effectively handle the problem of uncertainty and class imbalance a newly emphasized model named Deep Maximized Entropy based Memetic induced Reinforced Learning Model is devised for agriculture drought prediction which involves in monitoring the climatic ailment of the eight different districts in India.

2. Related Work

Tian et al [5] in their work to evaluate the correlation among soil moisture and drought class variable to predict the agricultural drought in river basin of Xiangiliang. The authors used precipitation evapotranspiration index is used for determining agriculture droughts. The climate indices with support vector regression is used to forecast drought in agriculture. To assess interannual changeability in agricultural output, Francisco et al [6] created two distinct prediction models. To forecast all units, an optimum linear regression and multilayer feedforward neural network were utilized in a single spatiotemporal method.Aishwarya et al [7] designed three different methods such as static, dynamic and hybrid to predict the presence of drought. They used variable of local climate, large scale indices and initial condition of land. Support vector machine is used for predicting meteorological drought prediction. The parameter used for drought prediction is rainfall and precipitation.

Fung et al [8] devised variant of Support Vector Regression (SVR) to predict the drought in agriculture. The fuzzy-SVR and boosted-SVR is used to predict standardized precipitation evapotranspiration indices. Anteneh et al [9] in their research performed short term prediction using three machine learning algorithms, support vector regression, traditional artificial neural network and couple wavelet artificial neural network. The wavelet transformation preprocessing is used for representing drought index.

Nourani et al [10] proposed a data mining approach using threshold-based hybrid model for forecasting perception based on long term. For classification and selection of the most effective groups is accomplished by decision tree approaches and extracts the hidden knowledge using association rules from the huge observed data.Inoubli et al [11] in their work assessed drought monitoring by utilizing remote sensing data. In their detailed survey they reported without accurate prediction, it is not possible to efficiently manage drought prediction. Aghelpour et al [12] designed a dragonfly algorithm which optimize the performance of the SVM for drought prediction. The meta innovative model palmer drought severity index to achieve robust agriculture drought prediction.Fadaei et al [13] devised k-nearest neighbor modelling to predict drought incidence based on the standard precipitation index (SPI). The precipitation data is used to test the model. The results suggest that the model is capable of making accurate forecasts about the drought status in the region.

3. Background Study

3.1 About Entropy

In information theory, entropy is used to measure the disorder in a system, when the entropy is high the problem of uncertainty will be decreased. The entropy computes amount of information acquired from the random variable to denote an event drawn from probability distribution [14]. The random variable A can be calculated using the formula

E(A) = $\sum_{o=1}^{n} Pb(a_i)(pb(a_i))$

In this agriculture land climate dataset L, the entropy is concerned with observing its instances and determining those features that provides the most gain in information. The entropy of feature f whose range of values are $(f_{1,...,}, f_m)$ regarding the dependent variable C with two possible values presence or absence of drought is represented as

$$E(F) = \sum_{k=1}^{m}\sum_{j=1}^{n} Pb(c_j|f_k)(pb(c_j|f_k))$$

Where n is the number of instances in the dataset and m is the number of features. C denotes conditional feature and fF is the decision feature.

3.2 Reinforcement Learning

Reinforcement learning is a subset of artificial intelligence that uses a reward and penalty scheme to build and train algorithms [18]. Instead of getting explicit instructions to accomplish its work, reinforcement learning provides a solution by itself. For learning processes Markov Choice Procedure is explored. During its learning process, RL acts as an agent by sharing and responding with the environment as shown in the figure 1. Based on their correct and wrong acts, the agent will be awarded or punished. RL learns without the help of humans by increasing rewards and limiting penalties.

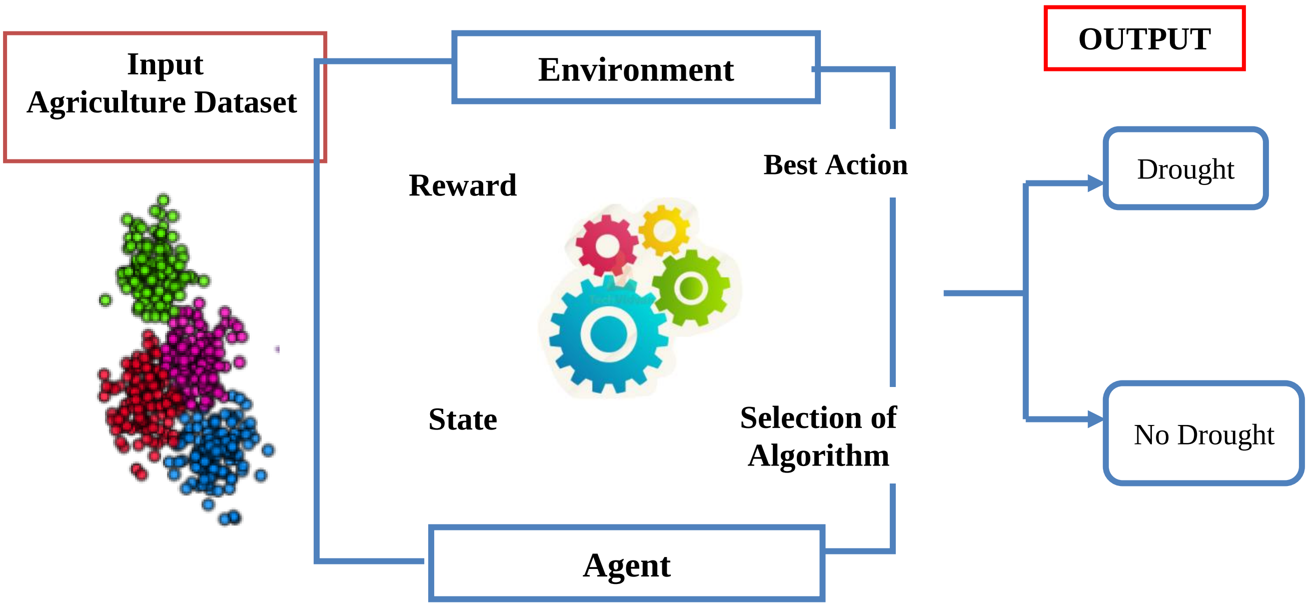

Figure 1: Workflow of the Reinforcement Learning (RL) Process

In RL, the elements are defined as follows

Agent – is an entity which perceive the environment and act accordingly
Environment – Agent present situation
Action- An agent's actions are the decisions he or she makes in the context of the environment.
State - After each action done by the agent, the environment returns a state to the agent.
Reward - The environment provides input to the agent, which is used to evaluate the agent's actions.
Policy - The agent receives information from the environment, which is used to assess the agent's activities.

3.2.1 Proposed Methodology: Deep Maximum Entropy with Memetic Reinforcement Learning Approach for Agriculture Drought Prediction: As the extension of the previous work [15], after clustering Agriculture dataset [16] by chaos genetic Intuitionistic fuzzy Subtractive clustering, the process of predicting presence or absence of drought is improvised in this proposed work by devising an information gain-based reinforcement learning prediction model. The main objective of this work is to handle the issue of class imbalance in agriculture dataset which affects the learning rate of the classification model.

The deep maximum entropy is used to discover the feature in the agriculture dataset which can offer maximum information to improve the prediction rate of RL. With those reduced feature set, the reinforcement learning fine tunes its parameters by inducing the memetic optimization algorithm known as shuffled frog leaping algorithm. The virtual frogs search for the optimal values to be assigned to the parameters of the RL to handle the class imbalance prominently during training phase. With the fine-tuned parameters, the reinforcement model improves its accuracy rate in prediction of presence or absence of drought in dataset. The overall workflow of the proposed DME-MRL is illustrated in the figure 2.

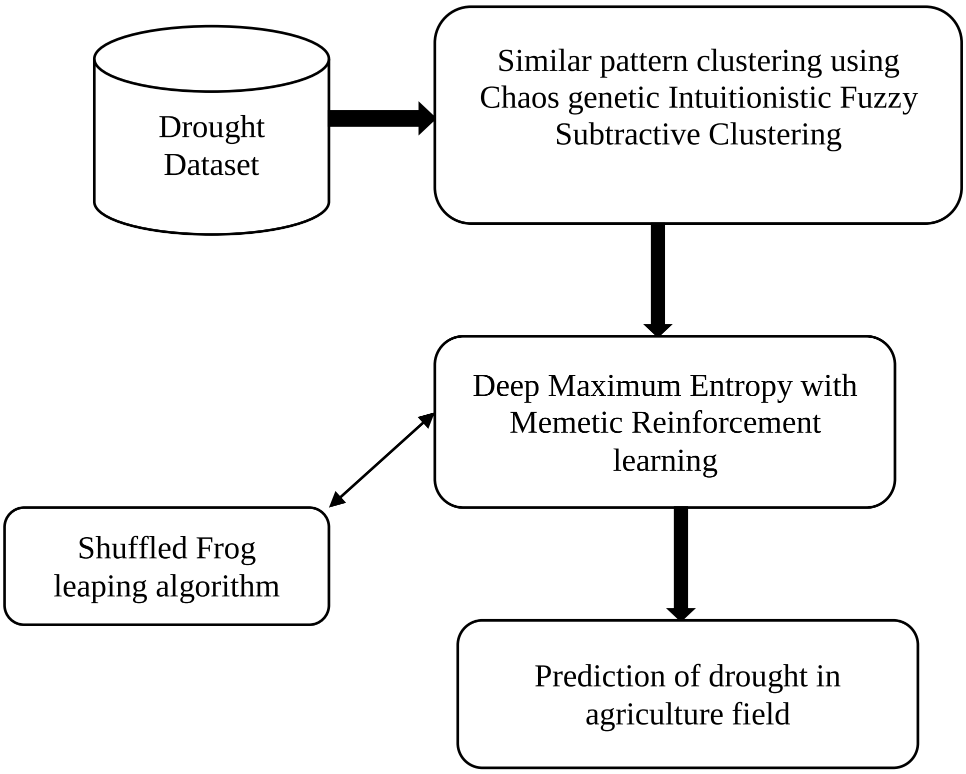

Figure 2: Overall Framework of DME-MRL for agriculture drought prediction

4. Dataset Description

The agriculture drought prediction dataset comprised of climatic condition of eight distinct districts of all over India with 11 attributes with 1536 instances [16]. Aurangabad, Yavatmal, Latur, Amaravati, Solapur, Pune, Nagpur and Nashik. The attributes year, month, district, temperature, average temperature, pressure, average pressure, rainfall and average rainfall are involved in the process predicting drought in agriculture land. In our previous work [15], the similar pattern of instances is clustered using Chaos genetic Intuitionistic fuzzy subtractive clustering was developed. In this work, the clustered pattern of dataset is fed as input to the proposed deep maximum entropy with memetic reinforcement modelling to improve the accuracy of agriculture drought prediction by tackling the issue of class imbalance. The deep maximum entropy method is used to discover significant subset of features based on the maximum information gain. The filtered subset of features is used by reinforcement learning algorithm to predict the drought presence or absence. But, the standard reinforcement leaning models face challenges in improving the learning rate during training of imbalanced dataset. Hence, in this work memetic based optimization algorithm known as shuffled frog leaping is induced in RL for fine tuning the parameter value of RL and thus it achieves highest rate of agriculture drought prediction.

5. Intuitionistic Fuzzy Subtractive clustering

As a continuation of the previous work [15], this proposed work starts with the clustered agriculture dataset as the input to the proposed DME-MRL. The Chaotic genetic algorithm based intuitionistic fuzzy subtractive clustering (CG-IFC) is applied on the agriculture dataset to discover the similar pattern of instances to predict the presence and absence of drought. The CG-IFC overcomes the problem of uncertainty by defining each instance in terms of membership, non-membership and hesitation degree. The selection of centroid is optimized in this work by adapting the chaotic genetic algorithm. With the optimized centroids, the problem of uncertainty in clustering the agriculture dataset instances more prominently.

6. Deep Maximum Entropy Reinforcement learning (DME-RL)

In DEMRL, the agent strives to improve the policy by selecting the best action that maximizes the total of rewards and lengthy aggregate of entropy. This allows the agent to go further into exploration and resist converging on local optima. It's crucial to grasp the maximum entropy concept before applying it to reinforcement learning. To understand better about the principle of maximum entropy, if there is a smaller number of probability distribution used for encoding previous data, then maximum entropy is obtained from the best probability distribution. In this work, to predict the agriculture drought the maximum entropy aims to discover the distribution which has maximum entropy. In conventional reinforced learning algorithms, an agent may converge to local optima. Meanwhile, if the maximum entropy is treated as the objective function, then the agents focus on searching with the maximum entropy distributions alone [17]. The existing problem in standard reinforcement model is, they reach their termination at its early stage of process due to local optima. Hence in this research work, maximum entropy is integrated with RL to learn the optimal policy in prediction of agriculture drought more accurately by attaining highest cumulative reward along with its entropy to be maximum. Thus, it provides the ability of more exploration and avoid converging to local optima. The traditional reinforcement learning [19] model's objective function is

$$OJ(\beta_\theta) = E_{\beta_\theta}(\sum_{t=0}^{T-1} \delta^t RL(s_t, a_t))$$

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After applying the maximum entropy with the help of objective function, agents can able to realize the best policy that can offer highest cumulative rate. By selecting right action, optimal policy has the possibility to produce highest cumulative reward

$$\beta^* = argmax_{\beta_\theta} E_{\beta_\theta}\left[\sum_{t-0}^{T-1} \delta^t RL(s_t, a_t)\right]$$

The maximum entropy reinforcement learning with the expectation of long-term entropy and reward is obtained by framing its objective function as

$$MOJ(\beta_\theta) = E_{\beta_\theta}\left[\sum_{t=0}^{T-1} \delta^t RL(s_t, a_t) + \tau H(\beta(s_t))\right]$$

The maximum entropy RL's optimal policy with highest expectation of long-term entropy and reward is denoted as

$$\beta^* = argmax_{\beta_\theta} E_{\beta_\theta}\left[\sum_{t-0}^{T-1} \delta^t RL(s_t, a_t) + \tau H(\beta(s_t))\right]$$

7. Shuffled Frog Leaping Algorithm

8.

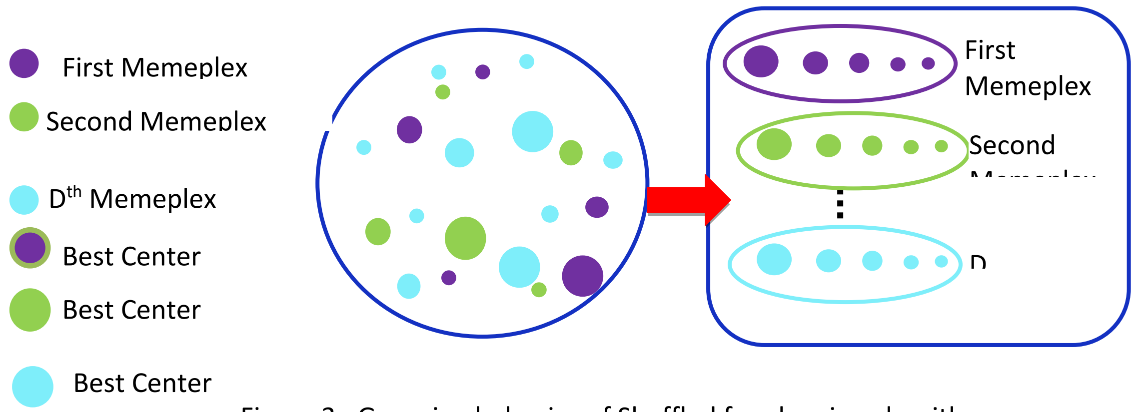

Figure 3: Grouping behavior of Shuffled frog leaping algorithm

One of the innovative memetic metaheuristic models is Shuffled Frog Leaping Algorithm (SFLA) which is designed by the inspiration of frogs leaping behavior during their searching its food [20]. The SFLA involves in this work to optimize the performance of Deep maximum entropy reinforcement model in the process of drought prediction. The features which contribute maximum information in the agriculture drought dataset is detected by applying the maximum entropy in attempt to optimize performance of the feasible search refinement process. Still, the learning rate of the DME-RL doesn't produce better results because of imbalance in dataset. To overcome this issue, SFLA incorporates the process of memetic and group optimization through local search among subgroups, to update the parameters of the lower level network which is known the standard reinforcement learning model [21]. Due to the simplicity and fast converging speed, SFLA is used as the optimizer in prediction of agriculture drought dataset by producing high rate of accuracy.

The whole population of virtual frogs is partitioned into subgroups, where each of them is sorted and spread throughout the solution space, in this work the weight matrix of the DME-RL, to select the best values for improving its learning rate in understanding the patter of instances with drought and non-drought labels. Let us consider there are M number of frogs with P number of problem size, ith frog position is mathematically modeled as

FPi = (FPi1, FPi1, …, FPiP)

The M number of frogs are partitioned into d set of virtual frog's knowns as memeplexes which have same structure but their adaptability differs among each other. By computing each frog fitness value, they are arranged in descending order and evenly divided into d number of memeplexes {L1,L2,…Ld} with p number of frogs in each memeplex M = d x p. In the first memeplex, the 1st frog is assigned, 2nd frog is assigned in the second memeplex this process continuous till d number of memeplex. Once first round of assignment is completed, then again it starts from 1st to d number of memeplex, it continuous until p number of frogs allocated in d memeplexes as shown in the figure 3. The SFLA method, to search the best weight values from the weight matrix of DME-RL, it uses individual grogs objective function during each iteration by allocating them to distinct groups, where the worst frog M_{wst}^{t} has observed the performance of the best individuals (M_{bst}^{t}) in the concern memeplex. If there is no progress in searching behavior after following the best individual then it learns from global best individuals (M_{gbst}^{t}) of all the memeplex to accomplish the best searching solution to choose the parameter values of DEM-RL. Though, it is not possible to attain optimal solution then the worst individual (M_{wst}^{t}) is replaced by random individual from the entire population. The shuffling behavior of individuals is illustrated in the figure. 4

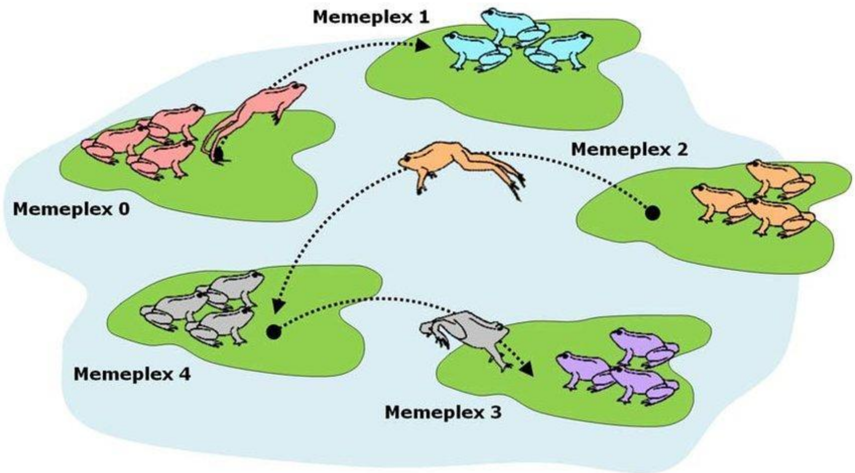

Figure 4: Virtual Frogs shuffling behavior

$MZ^{t} = VX\ (M_{bst}^{t} - M_{wst}^{t})$ eq (1)

$M_{wst}^{t+1} = M_{wst}^{t} + MZ^{t}(MZ_{r} \geq MZ \geq -MZ_{r})$ eq (2)

After updating the policy as denoted in the equation (2), the newly generated individuals is signified as M_{wst}^{t+1}, $M_{ws1}^{t+1}, M_{wst2}^{t+1}..M_{wstr}^{t+1}$. The moving step size of each frog is denoted as MZ^{t} within the leaping step value ranges amid $[-MZ_{r}, MZ_{r}]$. V is the random number with a disparity of [0,…,1].
If the newly generated individual M_{wst}^{t+1} is better than its prior value after updating, then M_{wst}^{t} is substituted by M_{wst}^{t+1}, otherwise M_{bst}^{t} is substituted byM_{g}^{t}. Still there is no progress M_{wst}^{t} will be substituted randomly by a new entity from the population. This is executed in an iterative process until the desired number of subgroups is achieved. When the subgroup task is finished, it will sort subgroups and split into new subgroups till the predefined endpoint is reached.

9. Deep Maximum Entropy based Memetic Reinforcement learning Model

Algorithm 1:

8.1. Deep Maximum Entropy based Memetic Reinforcement learning Model for agriculture drought prediction

Input: Agri Drought Dataset AD= {(z1,c1), (z2,c2),…,(zn,cn} // zi=1..n – records,c1..n- class label
Output: Prediction of Drought
Procedure

Begin
Initialize itr-max, θ
For a = 1 to itr-max do
Shuffle training dataset AD
Set state s1 ← z1
For t = 1 to T do
Select an action using deep-maximum entropy policy
at ←$\beta_\theta(s_t)$
rt,tmt ←(at,s_t)
Assign $s_{t+1}z_{t+1}$
Store (s_t, at, rt,s_{t+1}, tmt) to M
Shuffle (s_t, at, rt,s_{t+1}, tmt) from M
Perform SHFLA β^*w.r.t θ
Lθ$(y_j - Q(s_j, a_j;))^2$ // loss function
If tmi = true then
Stop
End for
End for
End

Algorithm 2: SHFLA(parameters a, s)
Procedure
Begin
Assign Population of frogs ← P
Assign No. of. Memeplex ← M
Select initial virtual frogs FRG V(1), V(2), … , V(FRG)
For j = 1 to FRG
Calculate fitness value of each frog V(j)
// Using mean value determine the distance of each individual as fitness value
Fit (V(i=1…FRG)) = dst (V(i) , μ(V(i=1…FRG))
Based on the fitness value sort frogs in descending order
End for
Divide population of frogs V(i=1..FRG) into M memeplexes
Develop submemeplex (SM) for each memeplex (M)
In each memeplex compute new position of the worst frog using the equation

$$MZ^t = VX\ (M^t_{bst} - M^t_{wst})$$

$M^{t+1}_{wst} = M^t_{wst} + MZ^t(MZ_r \geq MZ \geq -MZ_r)$ eq (3.3)
For i = 1 to SM
if (M^{t+1}_{wst} is better than M^t_{wst}) then $M^t_{wst} = M^{t+1}_{wst}$,
$if(M^t_{bst}$ not better than $M^t_{wst})$ then $M^{t+1}_{wst} = N^t_{gbst}$.
Else if $M^t_{gbst} isnotbetterthan N^t_{wst}$ then
N^t_{wst} will be replaced by swapping with a new frog from the initial population P
End for
Rejoin all the multiplex, go to step 5
Until the stopping condition is not met
Return (optimized (a))
End

The algorithm 1 and 2 describes the entire process of deep maximum entropy with memetic enforcement learning for agriculture drought prediction.

10. Simulation Results

The performance analysis of proposed deep maximum entropy reinforcement learning improved by memetic algorithm termed as shuffled frog leaping algorithm (DME-MRL) for agriculture drought prediction is deployed using python code. The agriculture drought prediction dataset comprised of climatic condition of eight distinct districts of all over India with 11 attributes with 1536 instances. The evaluation metrics used in this work are accuracy, precision recall and F-measure. The existing models used for comparison are MLP, ANN and SVM.

Table 1: Performance of Prediction Models for Agriculture Drought Prediction

	Precision	Recall	F-Measure	Accuracy
SVM	77.62	78.85	78.23	78.4
MLP	86.57	88.43	87.49	86.5
CG-IFSC	94.62	96.84	95.72	94
MDME-RL	97.1	97.69	97.39	97.2

The table 1 explores the comparative analysis of four different classification models involved in agriculture drought prediction. From the obtained results it is observed that the proposed model Deep Max entropy induced Memetic Reinforcement Learning algorithm (DME-MRL) explores highest rate of accuracy, precision, recall and f-measure in agriculture drought prediction. The SVM, MLP and CG-IFSC models suffer from class imbalance problem as it affects the learning rate of the classification model and thus they produce less performance while comparing with the proposed model DME-MRL. The CG-IFSC although handles the problem of uncertainty for discriminating the agriculture drought dataset, it uses the standard feed forward neural network to predict the presence or absence of drought. Hence, in this work the agriculture dataset after clustering by chaos genetic algorithm based intuitionistic fuzzy clustering, the clustered dataset is fed as input to the deep max entropy to discover the features which contribute more information to discriminate the drought and non-drought land area. The learning rate of the reinforcement learning model is enhanced by memetic based algorithm known as shuffled frog leap algorithm. 3312

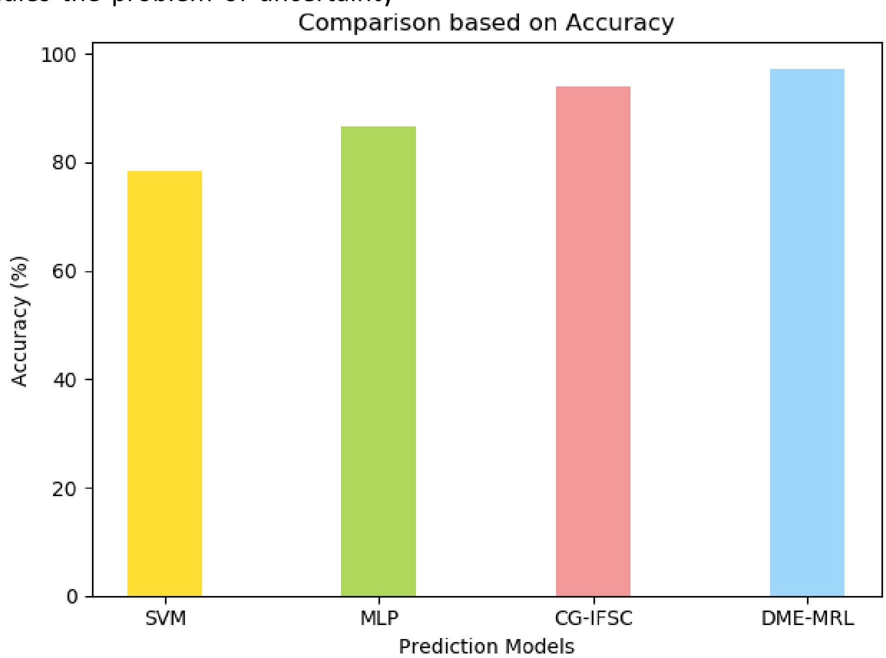

Figure 5 Comparison based on accuracy

$$Accuracy = \frac{No of instances correctly predicted as presence and absence of drought}{Total No of instance in dataset}$$

The accuracy rate of four different drought prediction model is exposed in the figure 5. The proposed DME-MRL accomplishes highest rate of accuracy compared to CG-IFSC, MLP and SVM. The reason is CG-IFSC after performing clustering process, the clustered information is validated using the feed forward neural network, which has the problem of class imbalance among the presence and absence of drought instance ratio. This affects the training process efficacy of CG-IFSC, MLP and SVM and results in less accuracy rate compared to DME-MRL. The proposed model DME-MRL handles this class imbalance problem by focusing on two important factors, evaluating the feature of the agriculture land drought dataset in terms of information gain to discover significant subset of features and improving the learning rate of the reinforcement model to attain its local and global optima by adapting shuffled frog leaping algorithm. The parameters in standard RL is handled by the greedy algorithm, which works under the trial and error basis to assign the parameter values such as weight and bias. This random assignment affects the training process of RL, thus SHFLA is used to search and pick the best values for the parameters which improves the learning rate of the RL by achieving balanced local and global optima in agriculture land drought prediction.

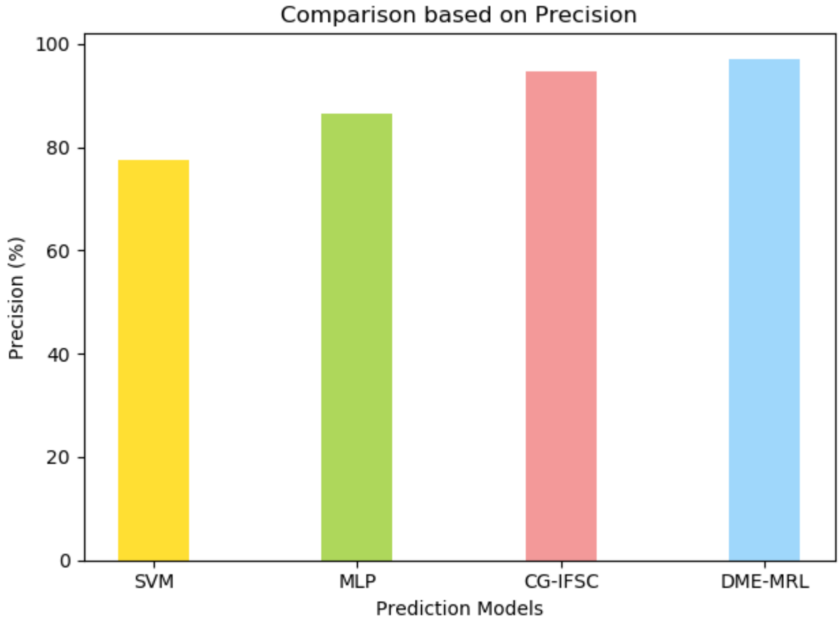

Figure 6 Comparison based on precision

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations.

$$\text{Precision} = \frac{\text{No of instances correctly predicted as presence of drought}}{\text{Total No of instances predicted as presence of drought}}$$

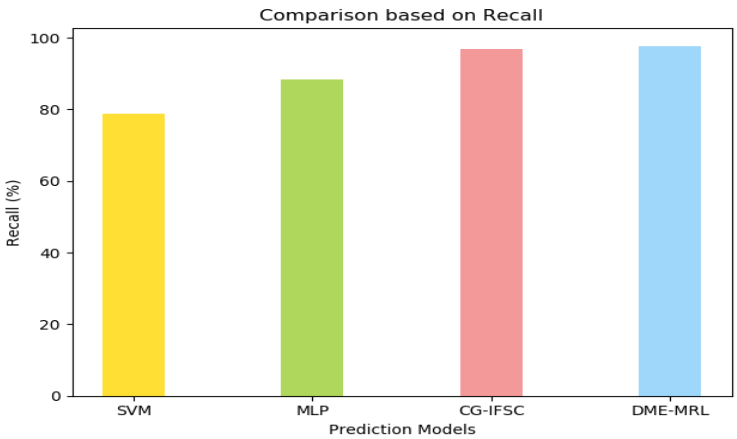

Figure 7 Comparison based on recall

Recall is the ratio of how many correct positive predictions were produced out of all possible positive predictions.

$$Recall = \frac{TotalNoofinstancescorrectlypredictedaspresenceofdrought}{ActualNoofinstanceswithpresenceofdrought}$$

The figure 6 shows the output of the precision rate generated by four different agriculture drought prediction classification models. The results illustrate the efficiency of the proposed model DME-MRL accomplishes higher precision rate compared to other three existing models in drought prediction. The DME-MRL correctly predicts the presence of drought by observing the clustered pattern of drought dataset with temperature, average temperature, pressure, average pressure, rainfall and average rainfall of eight different districts in all over India. The contribution of each features in the dataset is evaluated by applying deep max entropy method to detect significant features based on the information exhibited by them. Those features are used for training the memetic induced reinforcement learning model. The learning rate of the reinforcement model mainly relies on the parameters involved in processing the dataset. This proposed work DME-MRL utilize the shuffled frog leaping algorithm to assign the parameter values with the knowledge of shuffling and computing best fitness value for searching best set of values. For this reason, DME-MRL attains better rate of precision while comparing to the existing models SVM, MLP and CG-IFSC.

The four different drought prediction model's performance based on the recall metric is illustrated in the figure 7. The output of the results explores by focusing on identifying significant subset of features which highly contributes more information about dependent variable by predicting it. By finding the maximum entropy (ME) of each feature, instead of using entire features only the significant subset of features is used for prediction process. With the reduced feature set, the reinforcement learning model induce the knowledge of shuffled frog leaping algorithm, to overcome the issue of class imbalance problem when the ratio of instances with presence of drought is less than the instances with absence of drought. While class imbalance is not treated effectively during training of the classification model, then the learning rate will be greatly affected due to random assignment of parameter values by greedy method. Hence, this proposed work DME-MRL inferred the food searching behavior of the frogs, to choose the best values for fine tuning the parameters of RL. Thus, the recall rate of DME-MRL is better than the existing models CG-IFSC, MLP and SVM because they lack to handle the class imbalance in agriculture drought prediction.

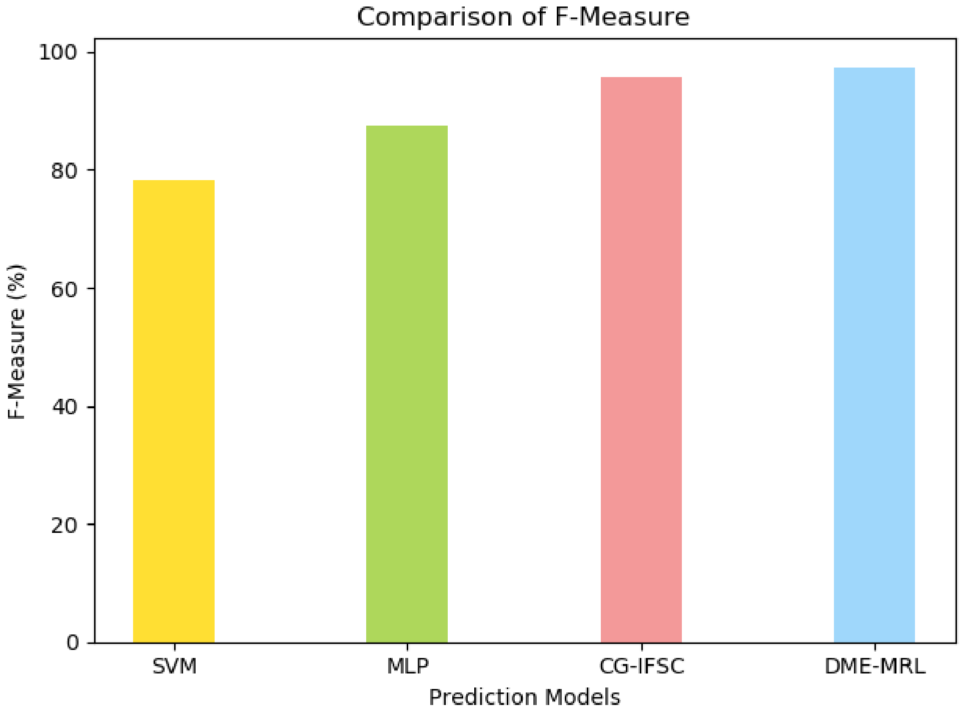

Figure 8 Comparison based on F-Measure

$$F - Measure = 2 * \frac{Precision * Recall}{Precision + Recall}$$

The figure displays the f-measure based performance comparison of proposed DME-MRL CG-IFSC, MLP and SVM involved in agriculture land drought prediction based on the climatic conditions. Since the f-measure value depends on precision and recall values, in this agriculture drought prediction the algorithm DME-MRL accomplishes highest f-measure value compared to CG-IFSC, MLP and SVM.

11. Conclusion

India is one of the top three crop producers in the world, so forecasting agriculture droughts is critical, as it gives planners with advance warning of potential threats, reducing the likelihood of drought impacts. The main objective of this paper is to design and develop an deep reinforcement model by extracting the maximum entropy of the policies to act accordingly and predict the presence of absence of drought in agriculture. The deep maximum entropy is used to discover the maximum information gain of the features in agriculture dataset and use them to understand the pattern of presence and absence of drought in agriculture. The training accuracy of the reinforcement learning is improvised by adapting the knowledge of shuffled frog leaping algorithm to optimize the class imbalance in drought dataset. The virtual frogs with highest fitness values are used for assigning the best values to the parameters instead of random assignment. Thus, the class imbalance in agriculture drought dataset is well handled by the proposed Deep Maximum Entropy based Memetic Induced Reinforcement Learning Model. The simulation results provide justified outcome of the proposed DME-MRL produced highest performance rate compared to SVM, MLP and CG-IFS which use ANN for validation.

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