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Enhancing Liver MRI Image Classification through an Innovative Hybrid Approach of Genetic and Social Spider Techniques for Effective Feature Selection

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KEYWORDS

Liver Diseases, Nature inspired algorithms, Genetic Algorithm, Social Spider Algorithm, Feature Selection, Hybrid Genetic and Social Spider algorithms. HGSS.

ABSTRACT:

One of the vital organs in the human body is the liver. A variety of diseases brought on by the organs' poor functioning every day include cirrhosis, hepatitis, and fatty liver. Many people's irregular eating habits, intake of alcohol, etc., are contributing to their development of liver illnesses. When it comes to the early identification and detection of liver problems, medical imaging is essential. Nonetheless, a major issue is accurately identifying essential features from medical imaging. The effectiveness of optimization methods inspired by nature is investigated in this study regarding feature selection for hepatic medical imaging. In order to determine these strategies' applicability and efficacy in improving diagnostic accuracy, the study compares them with current methodologies. This study selects the most informative characteristics from liver MRI medical image datasets using Genetic and spider algorithm. A thorough comparative analysis is carried out to assess the algorithm's performance in comparison to conventional feature selection techniques as well as the other techniques of nature-inspired methods. To ensure compatibility with the chosen Hybrid Genetic and Social Spider [HGSS] algorithms preparing hepatic medical imaging datasets is part of the experimental procedure. Genetic algorithm is used to extract the best features from the MR images and the nature-inspired social spider optimization algorithm is used to optimize the selected features. Evaluation metrics are used to measure how well feature selection performs in terms of computing efficiency Accuracy, Precision, Recall and F-Score. The proposed hybrid approach was compared with the traditional Random Forest (RF) model for image classification. The proposed HGSS algorithm optimization of the feature selection with CNN layer with 32 filter size of 3 X 3 showed the performance better than the RF.

1. INTRODUCTION

The liver, which is the biggest functioning organ in the human system, is found on the right side. Significant liver disease and the human casualties that go along with it must be prevented by sufficiently protecting the liver against infections and risky behaviors like drinking alcohol. Using a range of diagnostic methods, to identify severe liver disease early and treat patients appropriately to avoid major risks to human life. Artificial intelligence and its methods are playing a major role in the early analysis of liver problems using liver images, such as whether it is damaged or not, through appropriate investigative methods including MRI, CT, ultrasound imaging, and biopsies. In this research the hybrid Genetic technique with social spider optimization techniques of the nature inspired algorithm [HGSS] will be used to do the proper optimization of feature selection and extraction of the liver MRI images from the ATLAS [1] dataset. But it might be difficult to retrieve essential information for an appropriate diagnosis because of the sheer quantity and complexity of data received from medical pictures. Choosing the most relevant and discriminative characteristics from these datasets is a critical first step in improving diagnostic precision and cutting down on computing overhead. Using traditional feature selection techniques to liver MRI datasets frequently results in difficulties. High-dimensional data may be difficult for these techniques to process, which could result in extra computing overhead, or the possibility of missing important details required for an accurate diagnosis. Our study investigates the possibility of optimization strategies inspired by nature for hepatic medical imaging feature selection. Algorithms that draw inspiration from diverse biological and physical phenomena, known as nature-inspired algorithms, have

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shown potential in addressing intricate optimization issues. Also, the work will help to reduce computational complexity related to high-dimensional medical imaging collections while improving the diagnostic accuracy of liver disease detection.

The best optimized and most relevant features picked or retrieved were only taken into consideration for the evaluation of the best accuracy performer in the liver image classification. So the feature chosen plays the most important role in the image classification to identify the early detection of liver issues. To do the proposed study implementation, extract or select the fittest characteristics of the liver from the images using Python codes for the hybrid algorithm approach which is Genetic technique is used for subset of feature selection and SSA to be employed for the optimization of feature selection. Through that, the performance will be compared with the traditionally used conventional feature selection performance, which already exists. By which the best performer will be evaluated.

The research paper contains various sections. They are as follows, Section I - Introduction, which explains the research. Section II - Related works of previous research contributions. Section III - Problem statement. Section IV- Existing Algorithms of Nature-Inspired Algorithm for Feature Selection. Section V - which explains Materials and Methods of the proposed methods ,architecture and algorithm [HGSS]. Section VI - Results and Discussion about the proposed model, Section VII- which is Conclusion of the research and Future Works and Section VIII is references.

2. RELATED WORKS

The feature selection work in their proposed model is suggested that nature-inspired algorithms, which also prevent superfluous characteristics that degrade performance. The methodologies SVM, eXtremeBoost, ANN, NB, CNN, and LR are among them. Out of six groups, the aforementioned ways will be grouped with three distinct algorithms, the remaining methods will be grouped similarly. The best-performing combination to identify liver problems will be determined by comparing the results of exhaustive classifiers of each method's performance in their group with other combinations of methods with their results [2].

Researcher's T. H. Pham and B. Raahemi [3], say that the finding the best subset of features to minimize a cost function is the aim of feature selection. Another name for this function is the optimization function. Typically, the goal of optimization is to reduce the variation of data points both before and after feature selection. For high-dimensional data, a thorough search for the ideal subset is practically impossible and computationally costly. Heuristics are experience-based methods for learning and solving problems.

Researcher's Abu Khurma, Ruba, et. al [4],in their study which address Feature Selection[FS], Nature Inspired Algorithms[NIAs] are used for feature selection, meta-heuristic optimization, and modification. study is to provide a road map and direction when the researcher's conduct new research in this field. This survey is based on 156 publications that were gathered and examined regarding NIA changes for FS problem resolution. Six reputable scientific databases were the primary sources of the information used in the search: Elsevier, Springer, Hindawi, ACM, World Scientific, and IEEE. It's evident from the research that NIA algorithms have been thoroughly studied in recent years in an effort to solve the FS dilemma. A total of thirty-four operators were examined. Chaotic maps are the most widely used operator. The last twenty years have seen a rise in the use of nature-inspired optimization algorithms because of their effectiveness and adaptability in addressing global optimization issues. Swarms of fish, birds, and bees provide biological behavior that serves as inspiration for these algorithms [5].

Swarm optimization algorithms are frequently employed for feature selection prior to the deployment of machine learning and data mining techniques. For single-objective optimization tasks, metaheuristic nature-inspired feature selection algorithms are utilized; however, their main drawback is that they frequently converge too soon, which has a negative impact on data mining. In this research, we use some of the current issues in feature selection to present a unique feature selection approach called Reinforced Swarm Optimization (RSO). This technique maximizes the reward of an excellent search agent and penalizes the subpar ones by integrating Reinforcement Learning (RL) with the popular Bee Swarm Optimization (BSO) algorithm. This hybrid optimization technique strikes a nice balance between exploring and exploiting the search space, making it more resilient and flexible [6].

A crucial stage in the classification process, feature selection has a direct impact on classification performance. In order to maximize the accuracy of classification, the method for choosing features examines the data to remove noisy, redundant, and unnecessary information [7].

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Previous related works feature selection and classification model results comparison.

Author's	Feature Selection Tools	Classifier	Accuracy	Dataset	References
Murugesan, S., et al	Three bio inspired Algorithm [CSO, KH, and BFO]	SVM	0.9048	UCI	8
Devikanniga, D et.al	GA	SVM	0.9549	Irvine machine learning dataset	9
Hajihashemi, Vahid, et. Al.	Whale Optimization Algorithm[WOA]	KNN	0.912824	ILPD	10
	WHO	KNN	0.812349	BUPA	
Ghoniem, Rania M	CNN	CNN	0.961	LiTS	11
Gorunescu, Florin, et al.	GA	ESVM	0.6203	Public Dataset	12
CİHAN, Mücahit, et.al	CNN	CNN	0.966	Selcuk University,Turkey	13
George, E. Ben et.al	ABC	ABC	0.94.5	Public Dataset	14
Neshat, Mehdi, et al.	CBR-PSO	CBR-PSO	0.9325	UCI	15
Md, Abdul Quadir, et al	Extra tree Classifiers with Univariate statistical tests	Extra tree Classifiers	0.9182	ILPD	16
A. Midya et al	DL	Inception V3	0.96	Public Dataset	18
Raj, R. Joshua Samuel, et al	Opposition Crow Search	DL	0.9522	Public Dataset	19
Ali, Mona AS, et al.	RFE-GB	RF	0.9666	Public Dataset	20

Table 1.1 Prior research contribution

The above table 1.1 shows the contribution of the previous researcher's work in the field of feature selection with optimization and classification model results. The mentioned works not yet met the expected results in the field of identifying the liver disease or not in the earlier stage of the human. So, in this research proposed model-hybrid approach of Genetic algorithm and Social Spider HGSS technique for the best optimized feature selection and CNN model for the classification of the liver image to detect the liver is damaged or not with higher rate of accuracy in the performance through best and most relevant features of the images.

3. PROBLEM STATEMENT

Long-Term Hepatic Disorders:

Liver illnesses are a major worldwide health burden that are becoming more common because of genetic predispositions, viral infections, and poor lifestyles. For prompt management and better patient outcomes, liver disease diagnosis and prediction are essential. Conventional diagnostic techniques could not give timely information for efficient preventive interventions and frequently rely on invasive procedures.

Diseases such as Cirrhosis, Fibrosis, Chronic Hepatic, Liver Tumour are more crucial stages of the illness. If not identified the sickness of the liver in the earlier stage, it may lead to casualty.

The primary challenge is to identify an effective optimized feature selection method that mitigates the risk of reducing prediction accuracy when integrating classifiers into the analysis pipeline. Efficiently selecting pertinent features from complex 3D-MRI is critical for enhancing classification accuracy.

Testing options available to identify liver illnesses are as follows:

Blood test and HCV Antibody test in blood, Ultrasound, Biopsy test, HCV Antibody test in blood Computer Tomography scan and MR image scan.

For the better way to identify the relevant features, which are more essentially required to do the proper and earlier prediction using classification model of the liver image is affected or diseased is needed, so the proposed hybrid algorithm social spider with genetic -nature inspired optimization techniques for effective feature selection in liver MR imaging model is an integrated framework for early detection and prediction of liver diseases, ultimately leading to more effective healthcare interventions and improved patient outcomes.

4. EXISTING ALGORITHMS OF NATURE INSPIRED ALGORITHM FOR FEATURE SELECTION

Feature selection:

A feature is an attribute that affects a problem or is helpful for the issue, and feature choice is the process of deciding which features are crucial for the model to be effective. The foundation of all machine learning procedures is feature engineering, which consists primarily of two phases, feature extraction and choosing features. Processes for feature selection and the extraction may have the same goal, but they are entirely distinct from one another. The primary distinction between the two is that feature extraction generates novel characteristics, while feature selection focuses on choosing a subset of the initial feature set. Feature selection is a technique to minimize the model's input variable by incorporating only pertinent data to lessen excess fitting.

Nature Inspired Algorithm:

Algorithms that are inspired by natural phenomena, such as swarm intelligence, biological systems, physical systems, and chemical systems, are commonly referred to as nature-inspired optimization algorithms.

Methods for optimized feature selection in medical imaging.

To do the medical image analysis, it is essential to extract pertinent information, minimize computing complexity, and improve diagnostic accuracy through optimized feature selection. Liver cancer is a possibly fatal condition that can only be cured with a multidisciplinary approach to treatment. A framework for the precise diagnosis of liver illnesses may be provided via machine learning, feature selection, and image processing. One of the elements that come together to form this group is image processing. The device functions most effectively when it is used to evaluate previously captured visual information. This article discusses the significance of feature selection on machine learning algorithms for the timely and precise identification of liver cancers [17].

Genetic Algorithms: This algorithm finds the best subset of features based on a fitness function that assesses how well a classifier performs while using various subsets of features.

Social Spider Algorithm: A new swarm algorithm called Social Spider Optimization (SSO) is based on the social spider's cooperative nature. Search agents in SSO are like a group of spiders that move together in accordance with the biological activities of the colonies.

Cuckoo Search Algorithm:

The Cuckoo Search method selects a random solution for each improvement loop after arbitrarily initializing the number of solutions. After applying a levy flight to the chosen solution, a random placement for the solution inside the population is chosen.

Particle Swarm Optimization: This method works well for a variety of optimal difficulties because it uses particles to move and interact with one another to improve solutions iteratively.

Ant Colony Optimization: Ant colonies locate feed in an efficient and effective manner, which is the foundation of ACO. Fundamentally, this behavior is the result of ants using chemical pheromone trails to communicate indirectly with one another and find the most direct paths between their nest and food supply.

RFE: Recursively fitting the model and eliminating the least significant characteristics at each stage is how the well-known RFE algorithm operates. Until the required number of features is reached, the procedure keeps going. With high-dimensional datasets, this approach is especially helpful.

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Random Forest Feature Selection: One ensemble learning technique that can be used to determine the significance of a feature is Random Forest. Researchers can determine which features in the dataset have the greatest influence by calculating the drop in model performance that occurs when each item is removed.

Principal Component Analysis: It is a reduction of dimension method that has feature selection applications as well. Researchers can then concentrate on the components that account for the majority of the variance in the data since it converts the original characteristics into a new collection of orthogonal variables known as principal components.

Convolutional neural networks: After automatically extracting hierarchical features from images, convolutional neural networks pick salient features from trained representations.

5. MATERIALS AND METHODS

HGSS-CNN Architecture:
In Figure 1.1-HGSS Architecture which applies Gaussian smoothing techniques to reduce noise and artifacts in the input 3D- MRI images. Enhance the contrast of the images using histogram equalization, which improves the visibility of details in the images. Normalize and standardize the preprocessed images to ensure consistent and standardized input for subsequent algorithms to do the feature extraction. Extract features from the preprocessed MRI images. This could involve the method Genetic Algorithm (GA) to do the feature subset, which leads towards the best features. Evaluate subsets of features using a classification model or another relevant metric to check the accuracy. Set up GA parameters such as population size, generations, crossover, and mutation rates. Using GA to search for the best subset of features that maximizes the fitness function.

Apply SSA to further refine and optimize the selected feature subset obtained from GA. Update positions of social spiders based on fitness values to enhance the quality of selected features. Implement optimization steps specific to SSA for feature improvement. Train a Convolutional Neural Network (CNN) classifier using the best subset of features obtained after GA and SSA.

The CNN model should take the selected and optimized features as input for classification. Evaluate the CNN classifier using the preprocessed, selected, and optimized feature subset. Calculate Accuracy, Precision, R-call, and F-Score and other relevant evaluation metrics for classification performance. Finally compare the obtained results with existing models or benchmarks to assess the effectiveness of the proposed architecture.

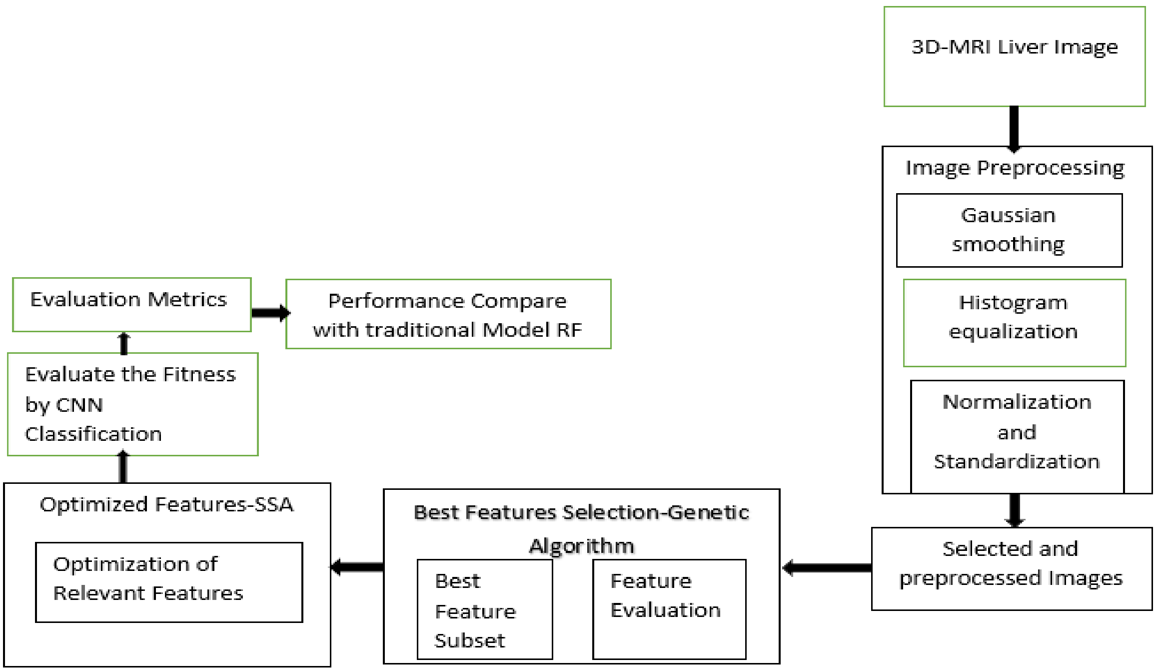

Figure: 1.1 HGSS-Achitecture

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Algorithm: 1: Hybrid Genetic and Social Spider [HGSS] Algorithm approach for best optimized feature selection

Input: Read the 3D-MRI Liver data

Step1: Preprocess the MRI data from the dataset to do.

a) Apply, Gaussian Smoothing,
   Smoothed Image = G * Original Image……………………………………………(1)
   where G is the Gaussian kernel

b) Apply, Histogram-Equalization,
   (CDF(OI)−min(CDF(OI))) / (Max(CDF(OI)−min(CDF(OI))) *irange……………(2)
   where CDF is the cumulative distribution function, OI is Original Image, irange is Intensity Range.

c) Apply, Reshape and alignment,

d) Normalize Image = (OI-mean(OI)) / std(OI)………………………………………(3)
   where OI-original Image, std is standard deviation

Step 2: Extract a set of features from the Normalized Images.

Step 3: Encode the features into binary strings to represent potential feature subsets.

Step 4: Initialize a population Q of feature subsets randomly.

Step 5: Define a fitness function that evaluates the performance of each chromosome using a classifier trained on the selected feature subset and evaluated using cross-validation or a validation set from the dataset.

Step 6: Set Termination criteria (e.g., maximum iterations, convergence criteria) for the GA.

Step 7: Repeat until convergence or termination criteria are met:

Step 8: Evaluate the fitness of each chromosome in the population using the fitness function.

Step 9: Select parent chromosomes for reproduction based on their fitness using tournament. selection or roulette wheel selection.

Step10: Apply crossover and mutation operators to create offspring chromosomes:

i. Perform crossover to combine genetic information of selected parents and generate new offspring chromosomes.

ii. Apply mutation to introduce random changes in offspring chromosomes to maintain diversity.

Step 11: Evaluate the fitness of the newly created offspring using the fitness function.

Step 12: Replace less fit chromosomes in the population with the new offspring.

Step 13: Select the best chromosome -feature subset- based on the fitness evaluation as the initial set of features for optimization.

Step 14: Use the selected features from GA as the initial input for the Social Spider Algorithm (SSA):

Step 15: Initialize the population of social spiders -feature subsets- with the selected best features from GA.

Step 16: Define an objective function based on the performance metric (e.g., classification accuracy) to optimize the feature subset further.

Step 17: Set termination criteria (e.g., maximum iterations, convergence criteria) for SSA.

Step 18: Repeat until convergence or termination criteria are met:

Step19: Evaluate the fitness of each spider -feature subset-using the objective function.

Step 20: Update the spider positions -feature subsets- using the SSA mechanism to explore the search space.

Step 21: Keep track of the best solution found during the optimization.

Output: Select the optimized feature set for medical image analysis on the 3D-MRI-dataset.

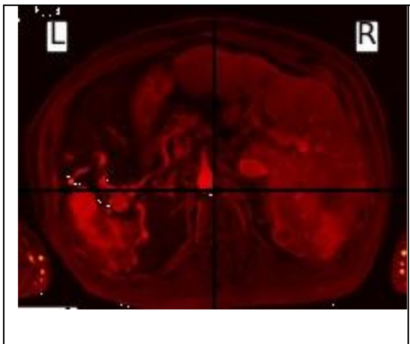

Figure: 2a) Raw MR image of Liver

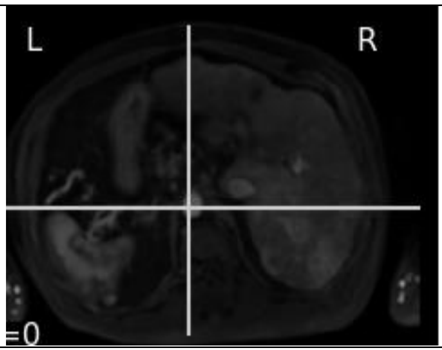

Figure: 2b) Smoothing-Gaussian

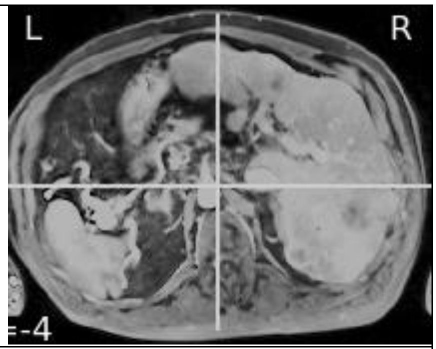

Figure :2c) Histogram

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The Figure 2a, is Raw MR image which is extracted from the dataset. Whereas the figure 2b and 2c are after applying the preprocessing are smoothing by Gaussian techniques, Histogram equalization techniques to attain the normalization of the MRI.

```
[[[0.12050696 0.         0.16103263 ... 0.         0.         0.03375197]
  [0.         0.06400963 0.07488724 ... 0.         0.08091457 0.        ]
  [0.02017033 0.         0.         ... 0.21354924 0.         0.        ]
  ...
  [0.04935582 0.0724731  0.17273192 ... 0.09673843 0.09742063 0.12668273]
  [0.04599291 0.03127857 0.03318707 ... 0.05990906 0.03876961 0.05730255]
  [0.05788971 0.06463002 0.03229264 ... 0.06697523 0.01594883 0.00709108]]]
```

Figure 3: Optimized Features-After Applying HGSS

In the above Figure 3, after applying the HGSS for the best optimized feature, the proposed algorithms give 376 features out of 784 original features, which are available in the 3D-MRI Liver images in the dataset. To do the best optimization techniques to reduce the features by using social spider algorithm to avoid unnecessary features through that to tune the performance with the high rate of accuracy can be attained.

6. RESULTS AND DISCUSSION

With the best optimized features by HGSS model, the attained performance for both trained the model with 40 images of the patients and tested the model with 20 images of the liver dataset, which is publicly available to attain the below metrics.

Acc = (CP+CN) / (CP+INN+CN+INP) …………………………………………………….. (4)

Pre = CP / (CP+INP) …………………………………………………………………..... (5)

R-call = CP / (CP+INN) ……..……………………………………………………………. (6)

F-Score = 2* (Pre * R-call) / (Pre + R-call) ……………………………….….…..… ……(7)

The equation 4,5,6,7 are used to calculate the measurement of Acc (Accuracy), Pre(Precision),R-call, F-Score, where CP-is Correctly identified Positive rate, INN-Incorrectly identified Negative rate, INP-Incorrect Positive rate, CN-Correctly identifier negative rate..
With the output of optimized feature set-it was trained and tested with the traditional model, which is Random Forest classification with HGSS, to predict the patient's liver has tumor or not, In the chart 1.1 the result shows are Accuracy, Precision, Recall and FScore are such as 0.9081,0.9009,0.8952,0.8979 respectively are generated using python program.

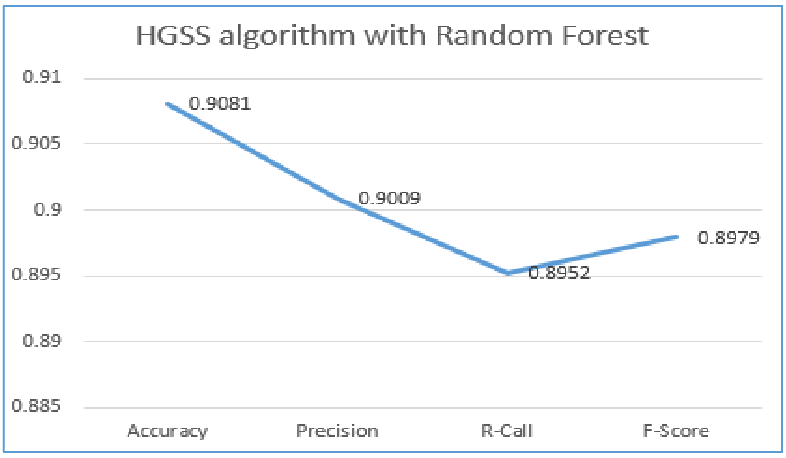

Chart 1.1-HGSS with Random Forest

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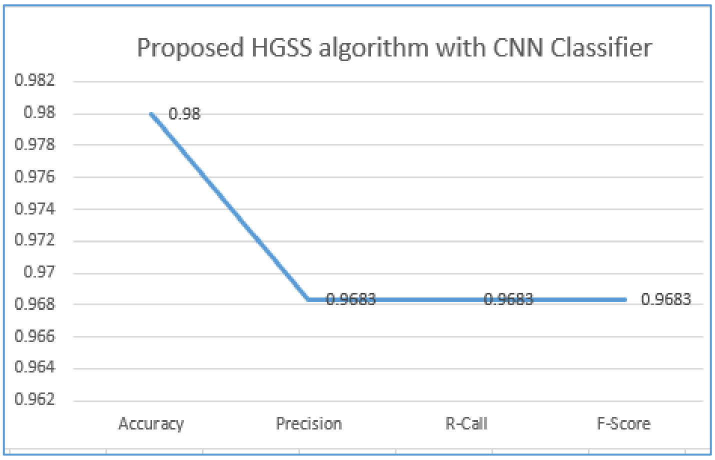

Chart:1.2 Proposed HGSS with CNN

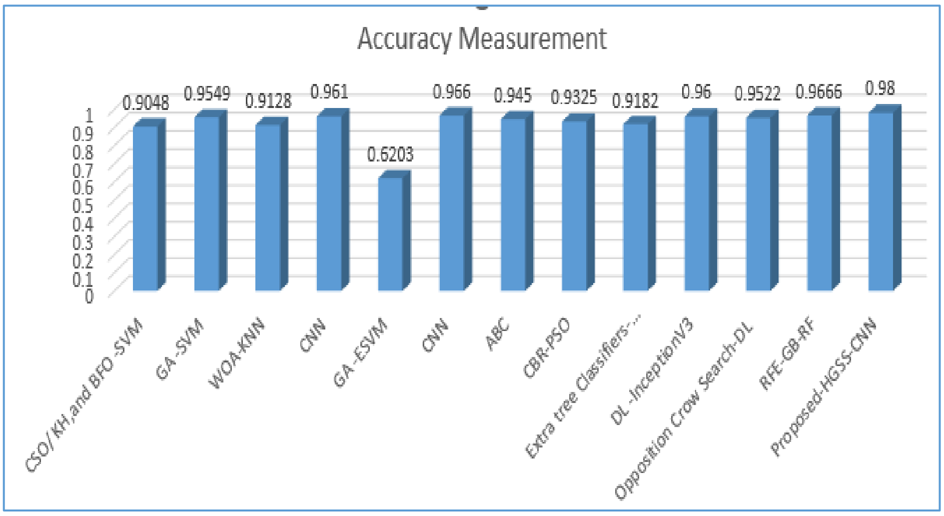

Chart1.3 Comparison of prior work with proposed technique

In chart 1.2 shown the performance of the proposed HGSS with CNN layer of 32 filter with size of 3 X 3 neurons to filtered input features 32 times, the max pooling layer to collect filtered features from CNN and ignore irrelevant features, it will send to next layer of the CNN. The Dense layer will be output layer, accordingly the CNN model to be trained with HGSS for the liver image classification of the person got affected with tumor or not, the model gives the results are such as 0.98 as Accuracy and 0.9668 as Precision, R-call and F-Score are respectively.

In chart 1.3, the proposed model HGSS-CNN shows better results than the other models. So, the proposed model will be helpful to humans as well for the physicians for the early identification of liver illness.

7. CONCLUSION AND FUTURE WORK

Feature selection is the important process to achieve the accuracy in the performance for the liver image classification of the patients, is affected or not. In this research, 3D-MR image of liver dataset is used, which contains 784 raw features, the HGSS algorithm is used to do the best optimized feature selection from the raw 3D-MR image. Finally, the optimized features sent to the 32 filter of 3X3 size layers of CNN model to do the proper classification of the liver image is damaged or not, the proposed model, which generated the accuracy is better than the traditional RF classifier. In the near future with the SSA for the feature reduction technique with three other CNN classifier will be used to predict the liver tumor using 3D-MRI, by which the best performer will be proposed. This will be helpful to the human as well to the radiologist and physician for the further treatment as

well for the early detection of the disease to save the life of the people in the world.

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Abbreviations:
GA-Genetic Algorithms
SSA-Social Spider Algorithms
HGSS-Hybrid Genetic and Social Spider algorithm

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CN-Correctly identified Negative rates.
CP-Correctly identified Positive rates.
INN-Incorrectly Identified Negative rates
INC-Incorrectly identified Positive rates
RF-Random Forest
CNN-Convolutional Neural Networks
MRI-Magnetic Renaissance Images
RF-Random Forest
DL-Deep Learning
SVM-Support Vector Machine
ABC-Artificial Bee Colony
PSO-Particle Swarm Optimization
ANN-Artificial Neural Network
NB-Naïve Bayesian
LR-Logistic Regression