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Leveraging Social Spider Algorithm for Liver MR Image Feature Reduction and Classification using GoogleNet, ResNet50, and VGG16 Models.

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ABSTRACT:

The liver is one of the most important parts of human life. Nowadays, everywhere on the globe, people's lives are affected by the malfunctioning of the liver organ. Due to many aspects of the non-proper day-to-day functions of the organs, such as fatty liver, cirrhosis, and hepatitis. Many humans' irregular diets, alcohol consumption, etc. are leading them to get affected by liver diseases. The mortality rate of the affected patients is high. Identifying the affected patients in their earlier stages by using common tests like biopsy, X-ray, CT scans, and MRI scans will help the physician do the proper treatments to recover from the deadly disease. In this research paper, we make use of medical MR scans of the subjects to apply three classification techniques to identify if the liver is healthy or impacted by illness. Also suggests a novel strategy that uses the Social Spider Algorithm (SSA) to reduce the features of MR images of the medical dataset. After feature reduction, the well-known CNN architectures GoogleNet, ResNet50, and VGG16 are used for liver image classification. The decreased feature set from the MR images that have been preprocessed and the SSA reduction technique are used to train and fine-tune the CNN models. Using a publicly available dataset of liver image data, the accuracy, precision, recall, sensitivity, specificity, and F1Score of 50 epochs with batch size-32 of each of the proposed CNN architectures are evaluated with and without SSA. The paper contributes to enhancing early liver disease detection by integrating the SSA for MRI feature reduction and exploring optimal CNN –GoogleNet-architectures for improved classification accuracy attained score is 99.41%.

Keywords: Liver Diseases, Nature Inspired Algorithms, SSA, ResNet50, VGG16, GoogleNet, Liver Image Classification

1. Introduction

For a variety of illnesses, magnetic resonance imaging (MRI) is a crucial diagnostic and monitoring method. It provides the detailed anatomical information required for accurate medical evaluations. When diagnosing liver disease, magnetic resonance imaging (MRI) can help identify liver issues early on by thoroughly examining the histology of the liver. Unfortunately, the enormous dimensionality and complexity of the obtained data sometimes render MRI imaging useless for disease diagnosis. The enormous quantity of information that can be extracted from these images is computationally expensive, which may make it more difficult to categorize diseases effectively. It is computationally demanding to extract the vast amount of information from these photos, which could complicate the process of accurately classifying diseases. Consequently, there is growing interest in capturing important distinguishing features and minimizing computing burden without compromising diagnostic accuracy with advanced data reduction approaches. Examining the efficacy of the Social Spider Algorithm (SSA) as a feature reduction method for liver image interpretation on MRI images is the aim of the proposed study. Social spider cooperation serves as the model for SSA, a metaheuristic optimization algorithm. It aims to imitate the cooperative hunting techniques and social dynamics displayed by social spiders. By using SSA, it is possible to retain crucial diagnostic information related to the diagnosis of liver illness while condensing the vast array of MRI features into a more manageable and informative subset. The study talks on two topics. Firstly, to investigate the extent to which the SSA preserves the crucial discriminative information required for the classification of liver disorders while reducing the dimensionality of MRI characteristics, Secondly, to evaluate the impact of the SSA-preprocessed decreased feature set on the CNN liver image classification performance. Three CNN architectures are GoogleNet, ResNet50, and VGG16 that are well-known for performing well on image classification tasks will be used in the current study. These CNN models try to improve early liver disease diagnosis by combining SSA for MRI feature reduction and looking into suitable CNN topologies for improved classification. The decreased feature sets from SSA-processed MRI images will be used to train and fine-tune them for liver disease classification. When compared to other models with SSA, GoogleNet accuracy outperforms in the study.

Nature Inspired Algorithm:

Nature-inspired optimization algorithms, as the name suggests, are algorithms that draw inspiration from natural phenomena including swarm intelligence, biological systems, physical systems, and chemical systems. (Wang , Qin , Wan , & Song , 2021)

Social Spider Algorithm:

The cooperative behavior of social spiders serves as the foundation for a novel swarm algorithm known as Social Spider Optimization. Similar to a swarm of spiders, search agents in algorithm move in harmony with the biological activity of the colonies (Luque-Chang , Cuevas , Fausto , Zaldivar , & Pérez , 2018). It would be interesting to find SSA real-world applications that can be managed well and affordably (James & Li VO, 2015).

Feature selection:

Feature selection is the process of identifying which features are necessary for the model to perform as intended. Machine learning procedures is feature engineering, which primarily consists of two steps are feature extraction and feature selection.

Classifiers:

The Classification method, a Supervised Learning technique, establishes the category of new finds based on training data. When a program utilizes classification, it classifies new findings into different classes or categories after first learning from the given dataset. (JavaTpoint, n.d.)

GoogleNet:
The Inception design serves as the foundation for convolutional neural networks of the GoogLeNet variety. The network can choose from a range of convolutional filter sizes for each frame by using Inception modules.
ResNet50:
As a result of their architecture, which resolved the vanishing gradient problem and made it possible to build networks with hundreds or even millions of convolutional layers, convolutional neural networks outperform shallower networks in terms of performance.
VGG16:
It has several layers and is a typical deep convolutional neural network architecture.

2. Related Works:

In the study the suggested method was able to segment the data while performing a steady insertion of the data, which created a link between the features produced by our network and the metric evidence of the data's complexity on the original manifold. This was made possible with a very light convolutional neural network with randomly initialized Gaussian weights. A ReLU activation function follows each convolutional layer, accelerating learning and causing early convergence. Furthermore, researchers substituted local response normalization for ReLU, which improved accuracy and lowered the false positive rate. Validation, using the benchmark datasets SLiver'07, 3Dircadb01, and LiTS17, for instance, demonstrates that their proposed model outperformed the others (Ahmad, et al., 2022).
It was classified patient medical images using six distinct approaches to determine whether the liver is disease-free or affected. Their technique uses algorithms inspired by nature to pick attributes, avoiding unnecessary traits that impede efficiency. Among these are the techniques SVM, eXtremeBoost, ANN, NB, CNN, and LR. Three distinct algorithms will be used to group the techniques out of six classifiers, the remaining methods will be categorized in a similar manner. By contrasting the outcomes of comprehensive classifiers for each technique's performance within its group with those of other method combinations, the optimal combination for identifying liver problems and recommending further therapy will be found (Ramachandran & Regula, 2023)

The SVMnet is a non-parametric image classification method based on a layered structure of Support Vector Machine ensembles, according to researchers, by utilizing SVMs' faster learning time than neural networks, the proposed technique can achieve higher accuracy than Deep convolutional neural network in scenarios when the training set is short. Experimental results show that whereas traditional of the same designs such as ResNet-50 perform better when the training set is larger, SVMnet performs substantially better (Goddard & Shamir , 2021).

To retrieve an accurate output image from the database based on the query image, the research study, present a succinct analysis and assessment of Multiclass SVM classifier, contrasting it with KNN classifiers. The suggested approach saves time and produces quality outcomes. By assembling these classifiers, we may build a system that is made up of many CBIR systems, each of which generates outputs that are complementary. We can find the optimal coordinate for the query image by combining these outputs. (Alimjan , Sun , Liang , Jumahun , & Guan , 2018).

The Research article, says that the offers several significant theorems and discusses their application to ensembles. Examine the effects of the number of component classifiers on these two types of ensemble methods. A few key features of both combination methods are touched upon in passing. A formula to find the optimal weights for weighted majority voting is also provided. Empirical research is used to verify the theoretical results. It believes that the results of their research will contribute to a deeper understanding of the principles of ensemble classifiers in general as well as the underlying features of these two combination strategies. Their examination of a few ensembles' classifier-related issues, such as diversity, ensemble pruning, ensemble performance prediction, and others, is aided by the findings (Wu, Li, & Ding, 2023).

The developed strategy to increase the prediction power of the conventional logistic regression model. They found that the simpler logistic regression model could be applied in two ways are by learning new, more complex features from the original input data that correspond to the explanatory variables associated with a given classification issue and by fitting a single-layered logistic regression model implemented by a neural network and fitting deep based models with multiple hidden layers (Tzougas & Kutzkov , 2023)

The research study, that project an automated method for TIC extraction and liver lesion classification in liver examinations using contrast-enhanced ultrasonography. The cohort consisted of 50 anonymized video examinations from 49 patients. Clinical data from the patients was provided in addition to the investigations. A three-module strategy was recommended. The first module used a Deep Learning model for lesion segmentation and handled frame-by-frame area of interest mask prediction. The next module applied a color map to extract the TIC and its parameters from the image after dilating the mask. In the third module, the feed-forward neural network made a prediction about the final diagnosis. It was trained with the TIC parameters. (Mămuleanu, et al., 2023).

A hybrid algorithm is utilized to recognize and distinguish between liver cancers based on MRI data. The wavelet's nature results in very little loss of the image's important characteristics. Consequently, the wavelet was used to extract important information from the image during the pre-processing phase. The speed and accuracy of the final result were significantly increased when PCA lowered the search space from 1024 to 20 (Gharakhanloo , Nakhjavanlo , & Mohammadi , 2018).

A method of classifying ultrasonic pictures of fatty liver that combines multiple image patching techniques based on pixel-level properties with a convolutional neural network proposed. It is capable of automatically identifying ultrasonic images of moderately fatty liver, severe fatty liver, low-grade fatty liver, and normal liver. The suggested approach increases classification accuracy while simultaneously resolving the issue of insufficient data. The experimental results demonstrate that, in terms of classification accuracy, our system performs better than both traditional methods and other deep learning methods. (Zhu , Liu , Gao , & Zhang , 2022)

Researchers designed accuracy-based weighted voting model, which includes feature extraction, classification, and data preparation. A novel accuracy-based weighted voting algorithm was proposed to improve accuracy in the final classification step, where two parameters and the model were introduced to improve accuracy and consumption time. Five M-CNN models with different depths and feature capture techniques were created to combine feature extraction (Ma, Xu, Han,, & Kim,, 2022).

3. Comparison and Analysis of previous works:

Year	Techniques Used	Accuracy	References
2018	Random Forest	80	(Haque, Islam, Iqbal, Reza, & Hasan, 2018)
	ANN -10 Fold	85.29	
2020	SVM(3D-H and B scan)	92.2	(Baek , Swanson , Tuthill , & Parker , 2020)
2021	Random Forest	83.7	(Ghosh, et al., 2021)
	ANN	94.12	(Musunuri, et al., 2021)
	DL-Regression-VGG19	80.1	(Kim , Lee, Park , & Choi , 2021)
	3D- ResNet-18	87.8	(Zhou, et al., 2021)
2022	CNN-SENet	95.27	(Chen , et al., 2022)
	CNN-Fusion net	72.46	(Dong, et al., 2022)
2023	DL- Segmentation with Coot Extreme	93	(Sridhar, C, Lai, & Kavin, 2023)
	Extra tree classifier and RF	91.82	(Naeem, et al., 2020)
	HGSSA-CNN	98	(Ramachandran & Regula, 2023)
	CNN	96	(Reddy & Ramkumar, 2023)
2024	ResNet with -5 fold	87	(Tangruangkiat, et al., 2023)
	CNN	97.7	(Gedeon & Liu, 2024)

Table 1.1

Table 1.1 compares and analyses the scientific contributions made in prior years to the diagnosis of liver illnesses, whether or not such data are available through the input dataset, which includes pictures from CT, MR, and ultrasound scans. by selecting or extracting the best features from the same set of input to be used in the images' subsequent classification. According to research conducted in the years 2023 and 2024, feature selection or extraction was carried out to perform the rating with a high ratio efficiency to detect liver diseases with the aid of liver images or its equivalent test using algorithms like social spider optimization with Genetic along with CNN classifications are efficient, based on the study of the highest accuracy as 0.98, above 0.96 as sensitivity, specificity, and Recall.

In the study of the previous research articles, approximately ten different datasets were used by the researchers to categorize whether the liver is affected. As a result, each of the classification algorithms like Random Forest(RF), KNN, CNN, DL , CNN-RSENet, 3D-ResNet-18, Fusion Net, DL-Modified Unet-60, DL with COOT, Densenet-DL, Extra classifiers, and Random Forest are to be listed in order of how the researchers used and achieved their results in their research. On the other hand, better accuracy performance was attained, and this is examined through the tabulation of table 1.1. results like 96% and above are the outcome of using SSA in conjunction with CNN, ANN, Random Forest, and Deep Learning.

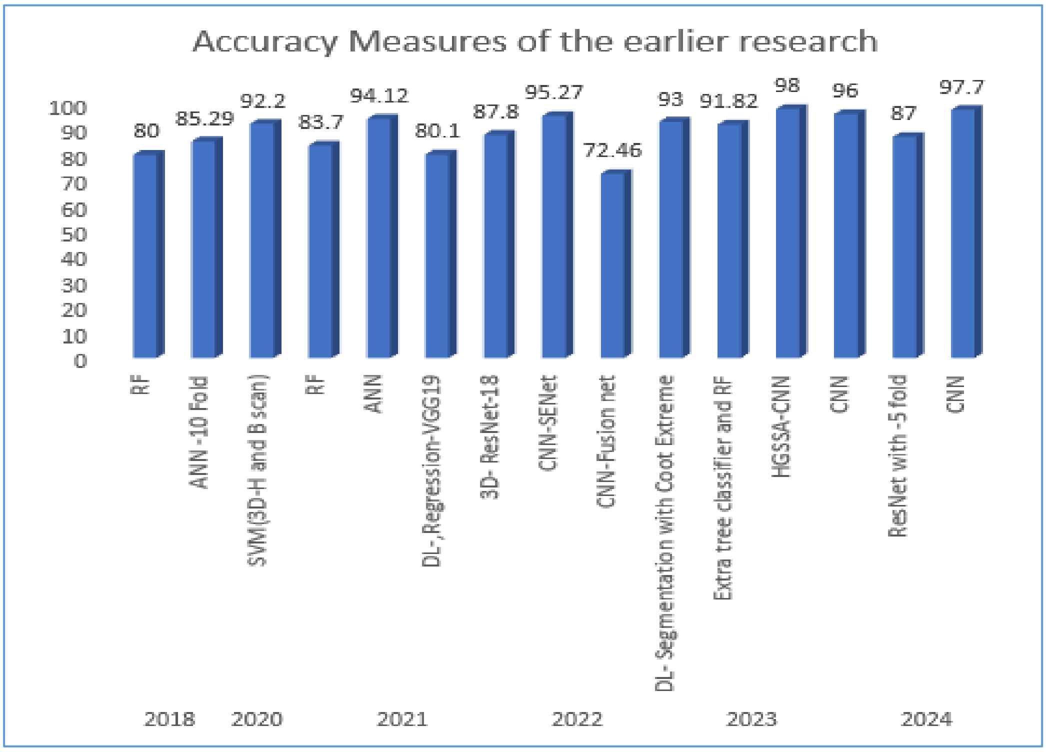

Chart1: Previous research contribution

The Chart1 illustrates the researchers' earlier research contributions from 2018 to 2024, showing that the HGSSA-CNN outperforms other models in terms of accuracy, with a notable 98% performance.

Given the circumstances, it would be reasonable to employ classifiers like GoogleNet, ResNet50, and VGG16 models in conjunction with the nature-inspired algorithm-social spider optimization technique to perform feature reduction and determine the person's liver image is damaged or not. When compared to other models, the suggested model yielded the significant results.

4. Materials and Methods:

Input of 3D-MR image dataset to be sent to do preprocessing using data normalization, equalization and reshaping techniques. The preprocessed of the dataset, SSA was applied for the feature reduction to get the best optimal features of the image, then the optimized features will be separated randomly for both training and testing in the ratio of 80 and 20 percent. Then the 80% of the images was trained in the models such as ResNet50, VGG16 and GoogleNet, As well as the remaining 20% of the image were sent to the model for the prediction of the liver image is affected or not. The performance of each models are observed, whereas the GoogleNet outperforms well. Also, with the same model it was trained and tested without SSA techniques, whereas it not performs well. The GoogleNet with SSA outperforms well as the attained accuracy as 99.41.

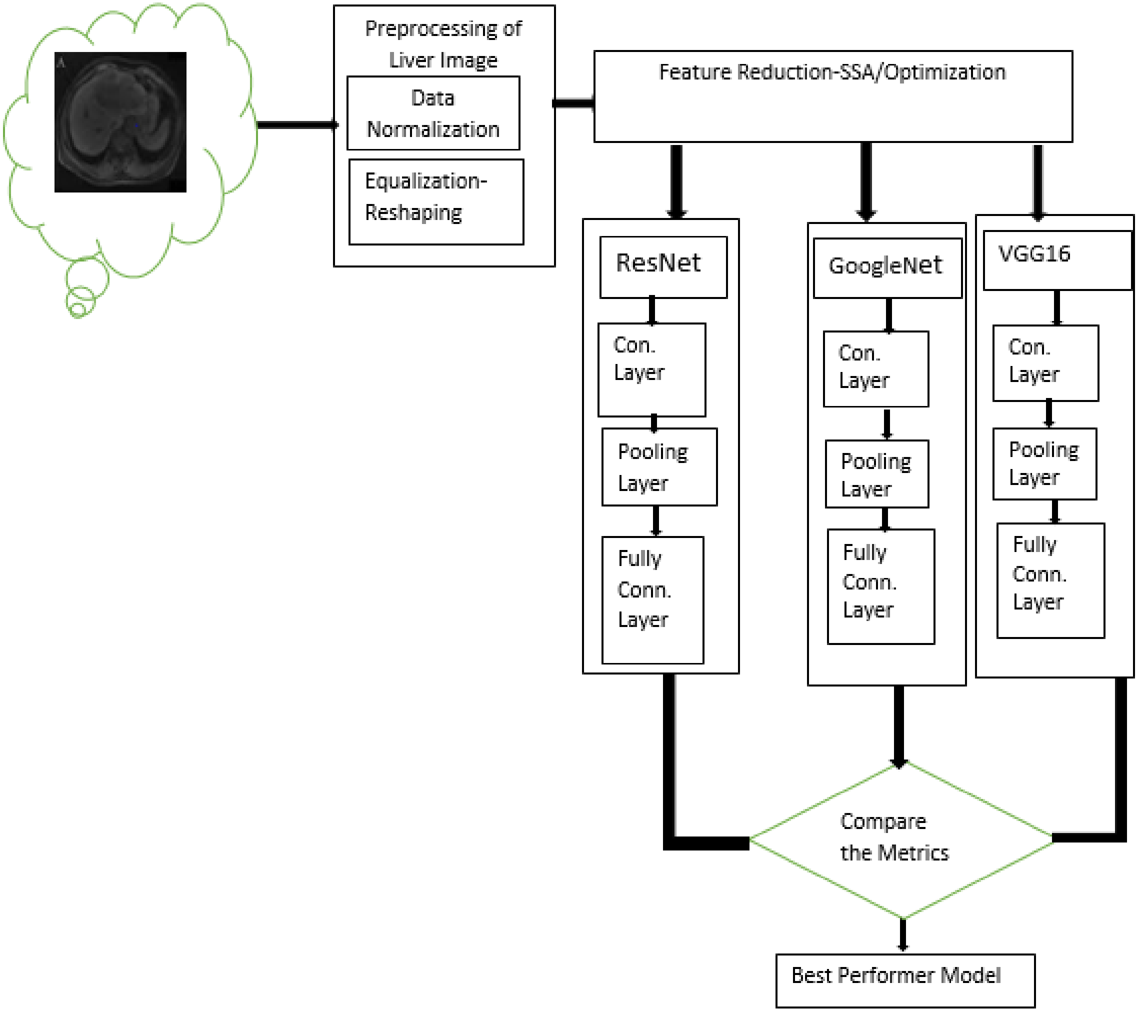

Fig:1: Proposed Methodology

Algorithm1: SSA with ResNet50, GoogleNet, VGG16
Step1: Input as MR Image Dataset.
Step2: Preprocessing of the Dataset.
a) Apply normalize the MR image.
b) Apply reshape and equalize the MR image.
Step3: The pre-processed data as input for Feature Extraction
a) Extract the relevant features from the preprocessed images.
Step4: Feature Reduction-social spider algorithm (SSA)
a) Employ feature reduction technique-SSA.
b) Initialize the Spider Position.
c) Set the maximum Iteration.
i. Obtain the feature subset.
ii. Evaluate the feature subset-increase the performance.
iii. Identify the best optimal subset of features.
Step5: Classification with ResNet50
a) Employ ResNet50 architecture.
b) Modified ResNet50 with Optimal subset features.
c) Train the dataset with ResNet50 Model.
d) Evaluate the trained model.
e) Testing to assess the classification resulted metrics.

i. Accuracy_R
ii. Specificity_R
iii. Sensitivity_R
iv. Precision_R
v. Recall_R
vi. F1Score_R

Step6: Classification with GoogleNet

a) Repeat the Step 5 : from a) to d) with GoogleNet
b) Testing to assess the measurement of the results.

i. Accuracy_G
ii. Specificity_G
iii. Sensitivity_G
iv. Precision_G
v. Recall_G
vi. F1Score_G

Step7: Classification of image with VGG16

a) Repeat the step 5: from a) to d) with VGG16
b) Testing to assess the performance.

i. Accuracy_VG
ii. Specificity_VG
iii. Sensitivity_VG
iv. Precision_VG
v. Recall_VG
vi. F1Score_VG

Algorithm2: Compare the VGG16, GoogleNet and ResNet50 Results

Higher_Accuracy = max (Accuracy_R, Accuracy_G, Accuracy_VG)………………....(1)
Higher_Precision = max (Precision_R, Precision_G, Precision_ VG)…………….…(2)
Higher_Recall = max (Recall_R, Recall_G, Recall_VG)…………………………..…(3)
Higher_F1Score = max (F1Score_R, F1Score_G, F1Score _VG)……………………(4)
Higher_ Specificity = max (Specificity_R, Specificity_G, Specificity_VG)………..(5)
Higher_Sensitivity = max (Sensitivity_R, Sensitivity_G, Sensitivity_VG)………….(6)

Step6: Nominate the best performer.

Best performing classifier to be selected based on the above equations (1), (2),(3),(4),(5) and (6) results attained.

Best_Performer_Model **= (** Higher_Accuracy, Higher_Precision,Higher_Recall, Higher_F1Score, Higher_Specificity, Higher_Sensitivity)

With respective of Algorithm1 and 2, the best performer model has been identified as GoogleNet for image classification with Feature reduction technique SSA ,which has produced the notable performance.

5. Results and Discussion:

Table 1.2 displays the performance outcomes for the suggested approach, without as well as with the use of the SSA reduction technique. The achieved score demonstrates that using the 3D-MRI dataset, GoogleNet with SSA techniques provided higher scores than VGG16 and ResNet50.

Model/Measurement	Accuracy	Precision	Recall	F1 Score	Sensitivity	Specificity
VGG16/SSA	99.02	99.1	98.89	98.89	99.69	98.13

ResNet50/SSA	93	92.66	93.91	92.91	88.78	99.05
GoogleNet/SSA	**99.41**	**99.43**	**99.36**	**99.39**	**99.69**	**99.05**
VGG16	70	79	66.46	66.9	97.9	35.08
ResNet50	71	81	67	70	98	37
GoogleNet	72	82	67.6	71.25	98.25	37.5

Table1.2: Proposed moded-performance metrics

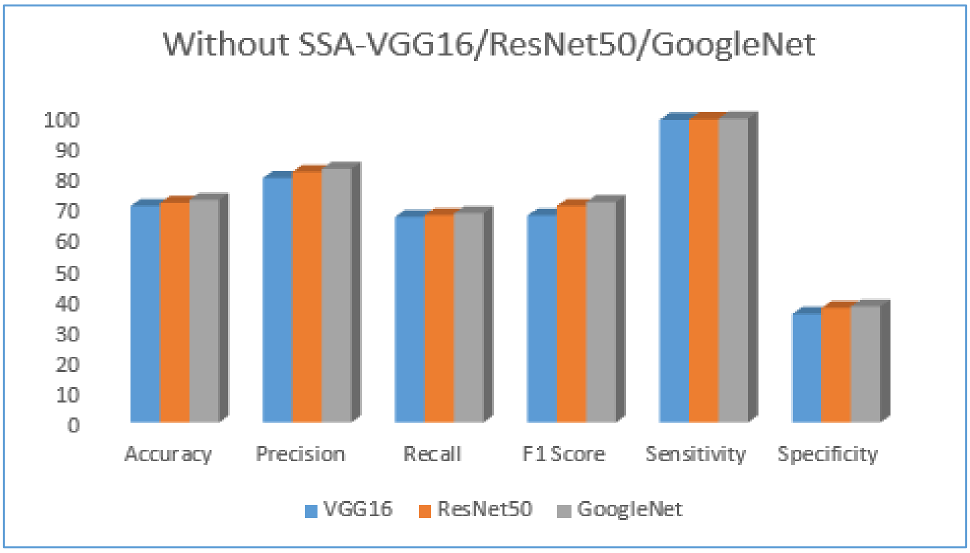

Chart2: Classifiers without SSA

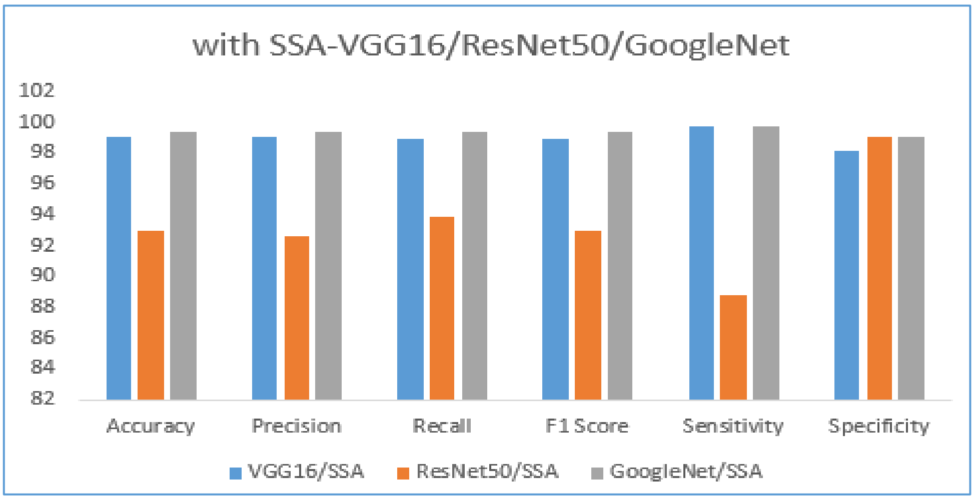

Chart3: Proposed classifiers-with SSA

The metrics that are achieved by applying the feature reduction technique of SSA with classifiers like ResNet50, VGG16, and GoogleNet using the medical MR liver image dataset as an input are shown in Charts 2 and 3. With 50 epochs and a batch size of 32, the updated GoogleNet performs better than the others in Accuracy, Precision, Recall, F1Score, Specificity, and Sensitivity, which are 99.41%, 99.43%, 99.36%, 99.39%, 99.69%, and 99.05%, respectively. Among the three proposed classification algorithms, GoogleNet with SSA exhibits the best efficiency. This means that individuals worldwide will benefit from early detection of liver illness and timely providing of life-saving medical care.

6. Conclusion:

The SSA of the patient's liver MR image from the publicly accessible dataset is used in this study to derive the optimal features. With 50 epochs and a batch size of 32, the classifiers ResNet50, VGG16, and GoogleNet are utilized to classify the liver image has affected or not. SSA-free classifiers were also examined. However, when the obtained results are compared, the SSA feature reduction strategy with GoogleNet classifiers did particularly well. As a result, the metrics that were obtained were 99.41%, 99.43%, 99.36%, 99.39%, 99.69%, and 99.05% respectively, for accuracy, precision, recall, F1score, sensitivity, and specificity. The GoogleNet with SSA technique will be useful for both the patient and the doctors in identifying the impacted liver and in treating sick patients worldwide.

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8. Appendices:

CNN-Convolutional Neural Network
KNN-K-Nearest Neighbour
DL-Deep Learning
SVM-Support Vector Machine
NB-Naïve Bayes
ANN-artificial Neural Network
LR-Logistic Regression
M-CNN-Modified CNN
SSA-Social Spider Algorithm
MRI-Magnetic Resonance Imaging
HGSSA-CNN-Hybrid Genetic SSA-CNN