Homomorphic Integral and Dual Rectified Convolutional Grading for Salinity Prediction During Seedling in Rice

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HOMOMORPHIC INTEGRAL AND DUAL RECTIFIED CONVOLUTIONAL GRADING FOR SALINITY PREDICTION DURING SEEDLING IN RICE

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Abstract

Rice is considered as one of the most sought out food crops globally. Salinity resilience plays an essential part in rice cultivation. But, uncontrolled saline level specifically at the seedling stage may unfavorable influence productivity of rice extensively. If not properly monitored, salinity stress brings about acute impairment during the seedling stage of crop growth bringing about an overall loss of 50%. Hence, it is mandatory to design an image classification and grading learning method for salinity stress analysis principally at the seedling stage and then benchmark its performance to circumvent depletion in rice yield. However, the classification using traditional method is both said to be laborious in terms of time and most of the time results in error owing to incorrect classification. To identify and classify salinity stress in rice seedlings using field images, the study reports the need of deep learning built model over traditional method of assessing rice crop's susceptibility to salt stress during the seedling stage. In this work, a method called Homomorphic Fourier Integral-based image classification and Dual Rectified Linear Convolutional (HFI-DRLC) grading learning for salinity stress level analysis in rice crops at seedling stage is proposed. Initially, an image enhancement framework that balances both field image features like as contrast, illumination and key properties that are important for identification of salinity stress level in rice crops at seedling stage. This is performed using Homomorphic Fourier Integral Filter-based Preprocessing model.

Next, Dual Rectified Linear Convolutional Neural prediction-based salinity tolerance in rice at seedling stage is designed to ensure both accuracy and precision. To investigate the effects of different improvement methods on the accuracy and precision of salinity tolerance in rice at seedling stage, comparison experiments between HFI-DRLC and traditional methods and comparison experiments with rice seedling dataset and rice seedling samplings from ICAR (Central Coastal Agricultural Research Institute, Old Goa, India) are executed. The method proposed in this study was shown to be more effective than traditional methods in terms of precision, recall, accuracy and error rate, providing a better method for salinity tolerance in rice at seedling stage.

Keywords: Salinity, Seedling Stage, Homomorphic Fourier Integral Filter, Dual Rectified Linear Unit, Convolutional Neural Network

1. Introduction

Despite rice being classified as a salt susceptible crop, it is not uniformly contrived all through its growth, being most susceptible at the seedling stages. All through the unblemished growth period, rice proportionately though found to be tolerant at germination, but growth becomes highly susceptible or sensitive during the early seedling stage (1–3 weeks). Salinity is the major stress that causes high susceptible therefore becoming a great menace influencing the global rice production sustainability.

An optimization strategy for seedling stage integrating both drought and salinity stress occurring in rice was proposed in [1]. Here, both the drought and salinity stress at the seedling stage was applied in a simultaneous manner by transplanting seedlings into saline soil. On the basis of differences and associations between physiological characteristics, the salinity stress treatment found to have greater influence on the rice plants, therefore improving stress reduction accuracy in a timely manner. Despite focus being made on accuracy aspect, timeliness remains a major aspects to be covered.

A Genome Wide Association Study (GWAS) and linkage mapping was combined in [2] with the purpose of analyzing candidate intervals for salinity tolerance in Japonica rice at the seedling stage.

This method took a look at the genetic process of salinity tolerance as evaluated by GWAS and linkage mapping based on the Na+ concentration in shoots (SNC), K+ concentration in shoots (SKC) and seedling survival rate (SSR) into account. With this integrated mechanisms detection rate of salinity in rice was improved in an extensive manner. Though salinity detection rate was improved in a significant manner, precision rate was not focused.

Agriculture industry is experiencing an expeditious digital transformation and is expanding vigorous by the pillars of cutting-edge mechanisms like, artificial intelligence (AI) and associated mechanisms. At the nucleus of AI, deep learning-based method validates several agricultural pursuits to be done in an automatic manner ensuring smart agriculture into reality. Computer vision methods in concurrence with high-quality image acquisition enable significant technology-driven solutions as far as agriculture is concerned. A review contributing to state-of-the-art computer vision methods based on deep learning that can help farmers from land preparation to harvesting was investigated in [3].

Despite rice being classified as a salt-sensitive crop, it is not equivalently influenced in every part of its germination being most susceptive at the seedling stage. In whatever way, a very poor association is said to have existence sensitivity at this seedling stage that recommends that the influences of salt are decided by distinct methods.

A review of different types of rice liberated for salinity tolerance characteristics those being monetarily cultured in salt strained soils and summarized phenotyping mechanisms in [4]. An in-depth validation of salinity tolerance at seedling stage using agro morphological data was investigated in [5]. One of the major food sources considered globally is rice. The insistence for rice will expand accelerated than other crops. Nevertheless, the global rice yield is extremely influenced by salinity stress. Soil salinity being one of the most is one of the most frequent environmental stressors are said to be pretentious by salt stress globally.

In [6], a detailed analysis and investigated on the influence of salt stress concerning both yield and grain quality for different variations in rice was presented in detail. Yet another review on Quantitative Trait Locis(QTLs) and genes analogous with agronomic yield-associated characteristics under drought stress was presented in [7].

Vegetation indices procured from high temporal resolution satellites using Moderate Resolution Imaging Spectroradiometer (MODIS) have the prospective in detecting soil salinity in a cost and time effective means.

An in-depth analysis of kharif salinity and rice crop behavior phenological measures in the process of distinct salinity levels was investigated in [8]. Yet another method employing Deep Convolutional Neural Network (DCNN) for recognition and classification of crop stresses employing field images was designed in [9]. With this type of design accuracy was said to be improved in a significant manner.

1.1 Contributing remarks

Taking into consideration the above performance factors and to address on the foregoing existing issues, in this work a method called, Homomorphic Fourier Integral-based image classification and Dual Rectified Linear Convolutional (HFI-DRLC) for salinity stress identification in rice crops at seedling is proposed. The essential contributions of HFI-DRLC method are listed below,

- To improve the precision and recall rate of salinity stress identification in rice crops at seedling, HFI-DRLCmethod is proposed. The HFI-DRLCmethod is introduced with the application of the image processing process and deep learning on contrary to existing work that used statistical analysis and genome-wide association mapping technique.
- To minimize the error rate involved in salinity stress identification, Homomorphic Fourier Integral Filter-based Preprocessing is applied to the input images that with the aid of sine and cosine transforms generates contrast-improved and illumination-free preprocessed image.
- To improve the precision and accuracy factor, Rectified Linear Convolutional Neural Network prediction algorithm is introduced that by employing Dual Rectified Linear Unit enhance the salinity stress identification accuracy.
- The performance was evaluated through extensive simulations with the rice seedlings dataset (i.e., obtained from repository and real time) and validated with the state-of-the-art methods.

1.2 Organization of the paper

The rest of the paper is ordered as follows. Section 2 portrays the related works in the field of salinity tolerance at the seedling stage in rice using machine and deep learning techniques. In Section 3, Homomorphic Fourier Integral-based image classification and Dual Rectified Linear Convolutional (HFI-DRLC) method is detailed with the aid of algorithm. The experimental settings are shown in Section 4 followed by detailed discussion in Section 5. Section 6 details the concluding remarks.

2. Related works

One of the major abiotic stresses that endanger the global rice production sustainability is the level of salinity. It has been evaluated that major certainly beneficial agricultural land is impracticable for sprouting rice both in Southern and South East Asia owing to high salinity levels. Different types of screening mechanisms for distinct morpho-physiological characteristics have been utilized for measuring rice salinity tolerance.

In [10], image based phenotyping protocol was designed with the purpose of analyzing two rice salinity tolerance characteristics. Moreover, rice response to distinct salt stress levels was measured and validated over time on the basis of total shoot area and senescent shoot area. The validation was performed based on the red, green and blue channels. With this there ensured discrimination between distinct features of salt stress was made in an accurate and precise manner. Yet another theoretical basis associated with salinity tolerance in rice was investigated in [11]. However time series analysis was not performed. To address on this aspect, enhanced vegetation index was applied as a criteria for analyzing agricultural soil. Here by applying the Savitzky–Golay filter [12] ensured stronger associations with salinity upon comparison to the unfiltered data.

As far as saline environment is concerned, different methods are designed with the purpose of improving plant breeding efficiency.

Comprehending the salt tolerance genetics is considered both a laborious and time consuming task due to the presence of multiple genes and involvement of pathways. Over the recent few years, for plant updates and manipulation, genomics knowledge provide detailed insights by introducing salinity tolerance mechanism. In [13], Genome Wide Analyses mechanism was presented to study variations and functional effects for developing salinity-tolerant plants. Also a detailed analysis was made for salinity stress tolerance. A review of AI for designing climate-smart crops was investigated in [14].

One of the crucial unfavorable environmental stresses that severely restrict plant growth and crop productivity is salinity. Different varieties with salinity tolerance at seedling stage nurture a significant growth and productivity at early stages giving rise to healthy vegetative growth that safeguards crop yield. Innumerable genes linked with salt stress were analyzed in [15]. However temporal aspects were not covered. In [16], the temporal aspects involved in rice salinity employing genotyping and marker assisted backcross were analyzed. With this mechanism improved salinity stress at the seedling stage was ensured in an accurate and precise manner. However the demand for rapid and low-cost extraction from images was not provided. In [17], convolutional neural networks (CNNs) and digital images were applied in concurrence simultaneously to evaluate the rice seedlings growth, therefore minimizing the error.

An improved CNN employing stacking mechanism for salinity stress level detection was designed in [18]. Also with this type of stacking mechanism not only resulted in the improvement of accuracy but also ensured higher recognition rate. To focus on the specificity aspect, a multi-model ensemble mechanism employing deep learning was presented in [19]. Yet another extensive and complete review of utmost improvements on molecular mechanisms managing plant revamping and tolerance to salinity stress was proposed in [20].

From the above hypothesis, the contemporary research works investigated above are necessarily summarizing the requirement for novel image classification and grading learning model for salinity stress level analysis of rice crops. Thus in this work, it is concentrated to deliberately present Homomorphic Fourier Integral-based image classification and Dual Rectified Linear Convolutional (HFI-DRLC) method that confers on significant results for precise and accurate salinity stress level analysis with minimum time and error and therefore improving the precision and accuracy rate significantly.

3. Materials and method

3.1 Dataset description

The rice seedling dataset consists of both the Ground Truth images and RGB images. All the images and the ground truth images are placed in separate folders. Also, the ground truth matlab file associate Ground Truth images with RGB images and on the other hand, image labeling session matlab file contains the configuration information of labeled data. The dataset is split into training and testing sets to train and validate the salinity tolerance in rice at the seedling stage employing deep learning method. Table 1 given below lists the SES of salinity at seedling stage utilized in our work.

Table 1 Standard Evaluation Score (SES) of salinity at seedling stage

S. No	Score	Observation	Tolerance
1	1	Normal growth on leaf symptoms	Highly tolerant
2	3	Nearly normal growth, but few leaves whitish and rolled	Tolerant
3	5	Growth severely retarded, most leaves rolled	Moderately tolerant
4	7	Most leaves dry and even some plants dying	Sensitive
5	9	Almost all plants dead	Highly sensitive

In addition to the images used from the above dataset, in consultation with ICAR (Central Coastal Agricultural Research Institute, Old Goa, India), real time experimental rice seedling samples were collected and validated. The rice crop images were captured from the field directly using high definition camera in September 2022. Some of the predominant image data input parameters used for validation are dimensions of the image, number of levels per pixel, number of channels and number of images. Scientists and agricultural specialists label the images according to the respective grades 1, 3,5,7,9 constituting the image dataset. When the images are reduced to 224*224 pixels, the images are generated using augmentation technique. As part of the processing, the images for the Training and Testing phases are loaded. The photographs are labeled and maintained in an array. 30% of the data are used for testing, and 30% are used for training.

3.2 Homomorphic Fourier Integral-based image classification and Dual Rectified Linear Convolutional prediction method

Crop growth and productivity are said to be hypercritically contrived due to both biotic and abiotic stresses. As far as crops are concerned, these abiotic stresses are initiated by environmental influences like, drought, salinity and curtail crop production globally even at the seedling stage itself. Of these abiotic stresses, salinity has a considerable influence of crop productivity, including rice. Over the past few years, the CNN has exhibited the stirring results in several image classification and prediction tasks. In this work a method called, Homomorphic Fourier Integral-based image classification and Dual Rectified Linear Convolutional (HFI-DRLC) is proposed for salinity stress level detection in rice crops at seedling stage. Figure 1 shows the structure of HFI-DRLC method.

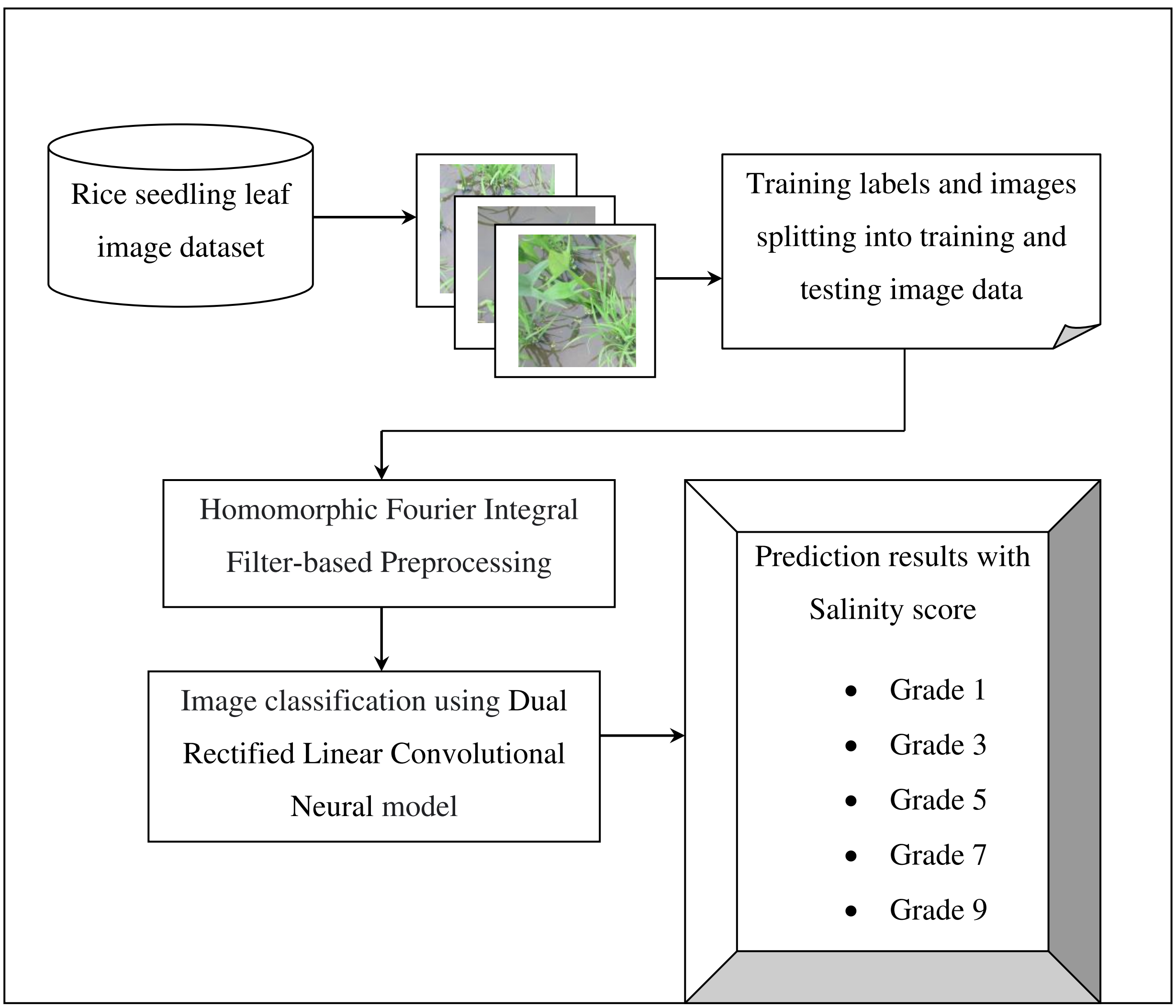
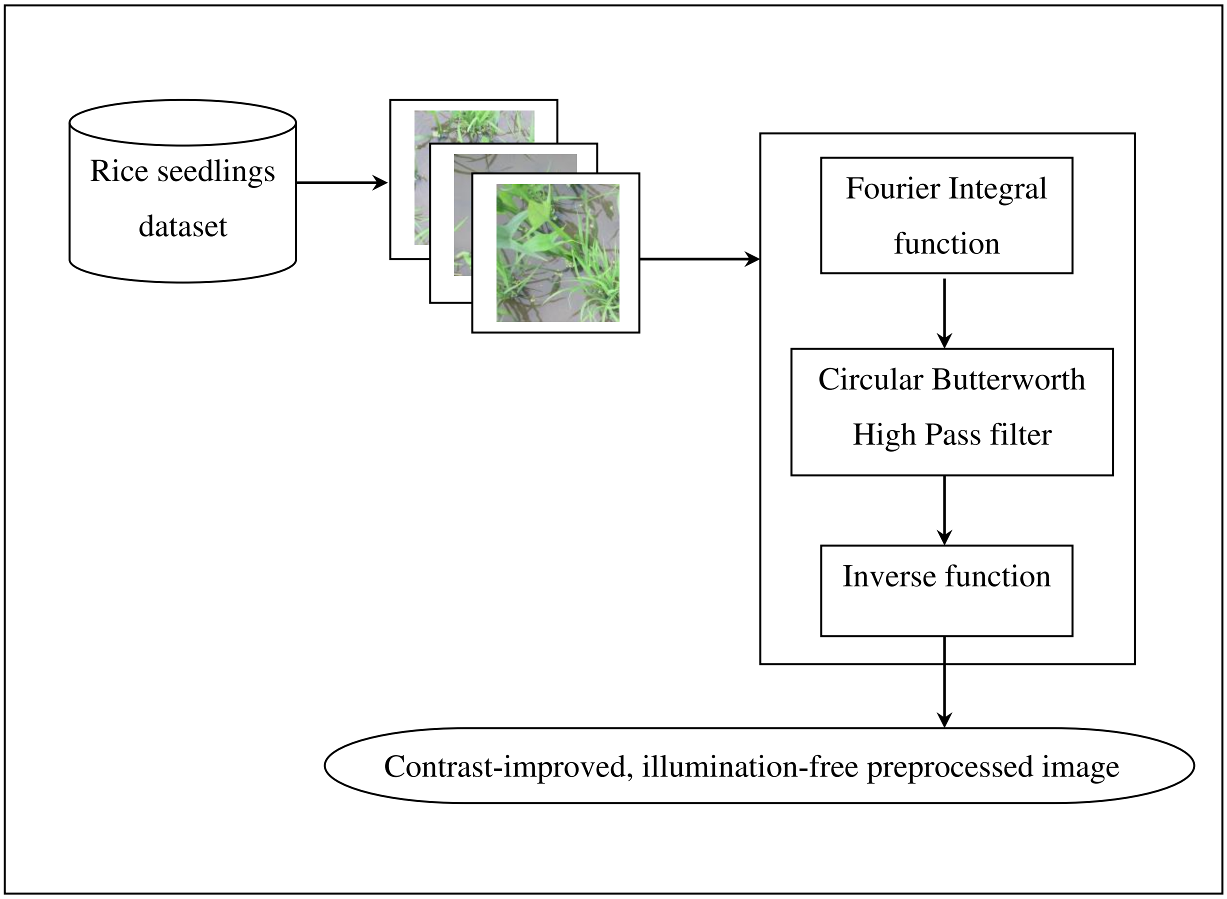


Figure 1 Structure of Homomorphic Fourier Integral-based image classification and Dual Rectified Linear Convolutional (HFI-DRLC) method

As illustrated in the above figure, with two rice seedling leaf image dataset acquired as input (i.e., one from kaggle and the other images acquired from real time) the overall training labels and images are divided into training and testing image data. With this training and test image data, two different processes namely, preprocessing and prediction is performed for salinity stress level detection in rice crops at seedling stage. Initially, Homomorphic Fourier Integral Filter-based Preprocessing model is applied with the purpose of generating contrast-improved and illumination-free images as output. Next, to perform prediction, Dual Rectified Linear Convolutional Neural Network prediction model is designed for obtaining accurate and precise prediction-based salinity tolerance in rice at seedling stage is designed. The detailed description of Homomorphic Fourier Integral-based image classification and Dual Rectified Linear Convolutional (HFI-DRLC) method is presented in the following sections.

3.2.1 Homomorphic Fourier Integral Filter-based Preprocessing

Image processing is growing imperceptibly in all fields of global agriculture especially in assessing rice crop's susceptibility to salinity during seedling stage. In order to increase rice seedling image quality while identifying and classifying salinity stress, preprocessing stages has to be applied. The foremost intend of the preprocessing approach is to improve the image classification and grading learning for salinity stress level in rice seedling images for visual assessment. To do preprocessing for rice seedling images, different approaches have been utilized by certain authors. In recent studies, the illumination and contrast enhancement via Homomorphic Filtering has been in used for the first step of preprocessing in rice seedling image region of interest detection. In our work Homomorphic Fourier Integral Filter-based Preprocessing is applied to enhance image enhancement that balances both contrast and illumination is initially proposed. The Homomorphic Fourier Integral Filter-based Preprocessing employed in our work is used for simultaneously performing intensity compression (i.e., illumination) and contrast enhancement (i.e., reflection). Figure 2 shows the structure of Homomorphic Fourier Integral Filter-based Preprocessing model.



model employed in our work assumes that the intensity of a rice seedling input image '$RI(p,q)$' be represented as the product of illumination '$I(p,q)$' and reflectance '$R(p,q)$' respectively as given below.

$$RI(p,q) = I(p,q)R(p,q) \tag{1}$$

From the above equation (1) 'p' and 'q' denotes the rice seedling image pixels spatial indices of the image pixels. As the Fourier's conventional transform of the product of two functions is not separable with the absence of complex numbers we define sine and cosine transforms as given below.

$$fun(t) = \int_0^\infty (p(\lambda)\cos(2\Pi\lambda t) + q(\lambda)\sin(2\Pi\lambda t))\, d\lambda \tag{2}$$

From the above equation (2), the functional integral '$fun(t)$' is formulated based on the coefficient functions 'p' and 'q' by means of Fourier Integral function with cosine and sine functions separately as given below.

$$p(\lambda) = 2\int_{-\infty}^{\infty} fun(t)\cos(2\Pi\lambda t)dt \quad (3)$$

$$q(\lambda) = 2\int_{-\infty}^{\infty} fun(t)\sin(2\Pi\lambda t)dt \quad (4)$$

$$Z(a,b) = fun_I(a,b)(t) + fun_R(a,b)(t) \quad (5)$$

With the above two formulate results as given in equations (3) and (4), the integral results '$Z(a,b)$' are obtained using '$fun_I(a,b)(t)$' and '$fun_R(a,b)(t)$' representing the Fourier cosine and Fourier sine transforms on illumination '$I(p,q)$' and reflection '$R(p,q)$' respectively. Moreover, 'a' and 'b' denotes the frequency indicators in the 'p' and 'q' directions. If the high pass filter is represented as '$HF(a,b)$', using Circular Butterworth then,

$$S(a,b) = HF(a,b)Z(a,b) = HF(a,b)fun_I(a,b)(t) + HF(a,b)fun_R(a,b)(t) \quad (6)$$

From the above equation (6), '$S(a,b)$' denotes the Fourier Integral results. Also, the first term due to illumination is anticipated to be attenuated by filter 'HF' and in a similar manner, the second term due to reflection or contrast is anticipated to be attenuated by filter 'HF' respectively.

$$HF(a,b) = (1-\alpha)\frac{1}{1+\left[\frac{Freq_{CO}}{Dis(a,b)}\right]^{2l}} + \frac{1}{\alpha} \quad (7)$$

From the above equation (7), Circular Butterworth High Pass filter '$HF(a,b)$' results are obtained using the cut-off frequency '$Freq_{CO}$' and the distance between the frequency indicators '$Dis(a,b)$' respectively. Converting back to the spatial domain is mathematically stated as given below.

$$fun(t) = 2\int_{0}^{\infty}\int_{-\infty}^{\infty} fun\,(T)\cos(2\pi\lambda(T-t)dTd\lambda) \quad (8)$$

Finally, the preprocessed output image is obtained as given below.

$$PI(p,q) = e^{fun(t)} \quad (9)$$

The pseudo code representation of Homomorphic Fourier Integral Filter-based preprocessing is given below.

Input: Dataset 'DS', Rice crop Images '$RI = \{RI_1, RI_2, \dots, RI_N\}$'
Output: contrast-improved and illumination-free preprocessed output image 'PI'
Step 1: **Initialize** 'N', '$\alpha = 3$', '$Freq_{CO} = 0.3$', '$l = 2$' Step 2: **Begin** Step 3: **For** each Dataset 'DS' with Rice crop Images 'RI' Step 4: Formulate product of illumination and reflectance as given in equation (1) Step 5: Evaluate Fourier sine and cosine transforms as given in equations (2), (3) and (4) Step 6: Obtain integral result as given in equation (5) Step 7: Evaluate Circular Butterworth high pass filter as given in equations (6) and (7) Step 8: Convert back to spatial domain as given in equation (8) Step 9: Generate preprocessed output image as given in equation (9) Step 10: **Return** preprocessed output image 'PI' Step 11: **End for** Step 12: **End**

Algorithm 1 Homomorphic Fourier Integral Filter-based Preprocessing

As given in the above algorithm, given the raw rice seedling images provided as input, the objective here remains in designing a preprocessing model so that accurate results are arrived at both computationally efficient manners with minimum error. First, product of illumination and reflectance is formulated for the raw rice seedling images. Following which, Fourier sine and cosine transforms or the Fourier Integral function is applied for producing integrated image pixels via Circular Butterworth high pass filters. Finally, the inverse function is applied for obtaining the preprocessed output image.

3.2.2 Dual Rectified Linear Convolutional Neural prediction-based salinity tolerance in rice at seedling stage

The suitability and drawbacks of the conventional methods necessity for salinity stress level detection in rice crops at seedling stage is of great practical significance to replace some tedious manual measurements.

The evolution of computer vision and utilization of deep learning (DL) technology is an efficient tool in improving the efficiency of control management and analysis of stress level in agriculture. One of the DL that is frequently utilized in solving image classification issues is Convolutional Neural Network (CNN). With the aid of CNN a significant level of accuracy is said to be achieved owing to high network depth and is able to analyze the features contained in the complex images (i.e., preprocessed output image). Therefore, in this work we carried out the study on prediction of salinity in rice at seedling stage using CNN. Figure 3 shows the structure of Dual Rectified Linear Convolutional Neural Network prediction-based salinity tolerance in rice at seedling stage.

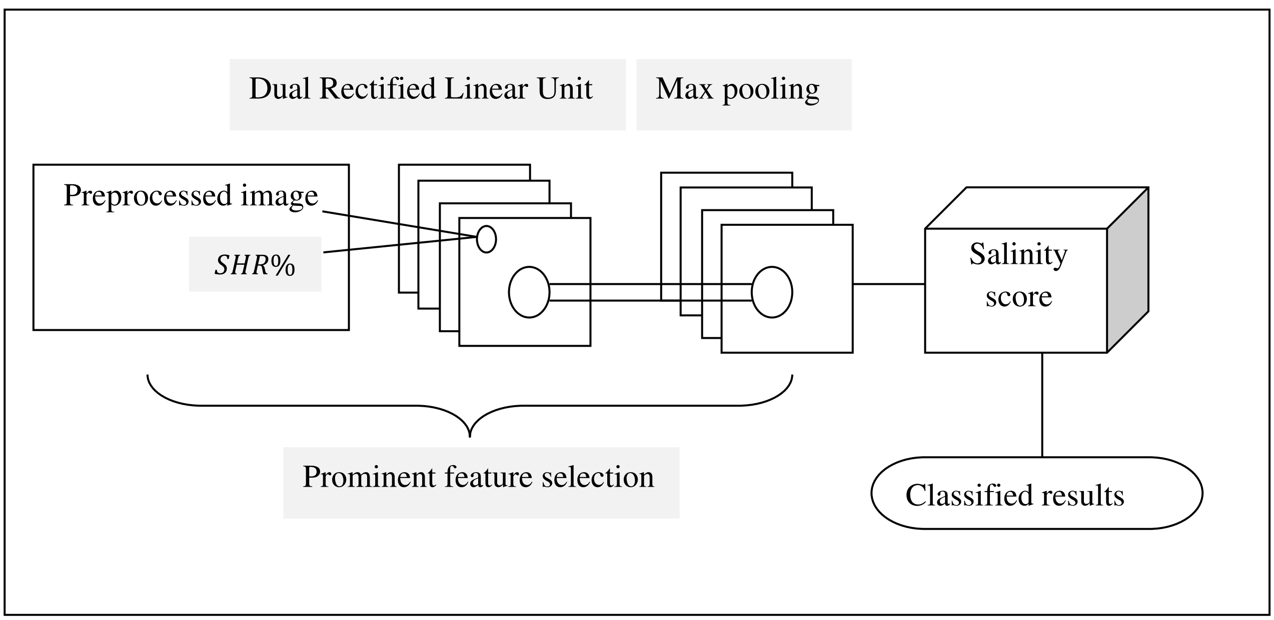


Figure 3 Structure of Dual Rectified Linear Convolutional Neural Network prediction model

As illustrated in the above figure, after 4 weeks of seedling salinity treatment, plant height, leaf width, leaf length, plant height at controlled level 'PH_{CL}', plant height at saline condition 'PH_{SC}' are investigated and accordingly, the seedling height reduction percentage '$SHR\%$' is measured as given below for each preprocessed image.

$$SHR\% = PI\left[\left(\frac{PH_{CL} - PH_{SC}}{PH_{SC}}\right) * 100\right] \tag{10}$$

With the seedling height reduction percentage preprocessed image of size '$m * n$', where 'm' denotes the number of rows and 'n' denotes the number of columns respectively.

The Dual Rectified Linear Convolutional Neural Network prediction model is split into distinct portions with each preprocessed image pixel the convolution operation is performed for three color channels, red, green and blue respectively. The matrix representation of each preprocessed image pixel for three color channels is illustrated as given below.

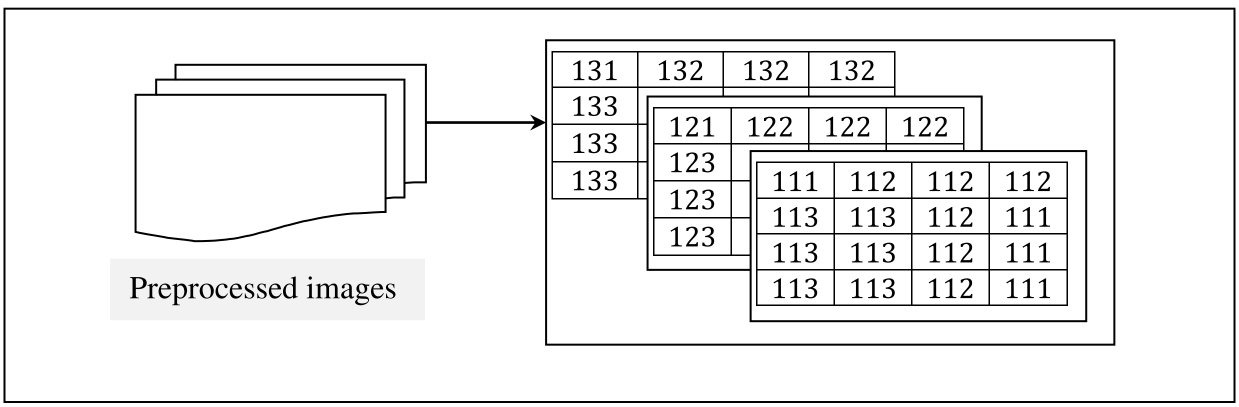


Figure 4 Preprocessed image matrix representations of three color channels

As illustrated in the above figure, the convolution operation of each preprocessed image pixel for red color channel is represented as given below.

$$PI_{red} = \begin{vmatrix} 0 & 0 & 0 \\ 0 & 131 & 132 \\ 0 & 133 & 133 \end{vmatrix} * \begin{vmatrix} 1 & 0 & 1 \\ 1 & -1 & 1 \\ -1 & 0 & -1 \end{vmatrix} \tag{11}$$

In a similar manner, the convolution operation of each preprocessed image pixel for green color channel is mathematically stated as given below.

$$PI_{green} = \begin{vmatrix} 0 & 0 & 0 \\ 0 & 121 & 122 \\ 0 & 123 & 123 \end{vmatrix} * \begin{vmatrix} 1 & 0 & 0 \\ -1 & 1 & 1 \\ 0 & 1 & -1 \end{vmatrix} \tag{12}$$

Finally, the convolution operation of each preprocessed image pixel for blue color channel is denoted as given below.

$$PI_{blue} = \begin{vmatrix} 0 & 0 & 0 \\ 0 & 111 & 112 \\ 0 & 113 & 113 \end{vmatrix} * \begin{vmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 1 & 1 & -1 \end{vmatrix} \tag{13}$$

With bias '$Bias$' initialized to be '1', the resulting feature map is mathematically represented as given below.

$$FM = PI_{red} + PI_{green} + PI_{blue} + Bias \tag{14}$$

Following which the next process remains in activating the above feature map results employing the Dual Rectified Linear Unit (DReLU). The advantage of using DReLU upon comparison to single activation function is that is comes along with both positive and negative image therefore circumventing the contingency of vanishing gradients when performing several convolutions to obtain the final predicted results. The DReLU being a two dimensional activation function results in three distinct states mathematically stated as given below.

$$f_{DReLU}(p,q) = \begin{cases} 0, if\ p \le 0\ and\ q \le 0 \\ p, if\ p > 0\ and\ q \le 0 \\ -q, if\ p \le 0\ and\ q > 0 \\ p-q, if\ p > 0\ and\ q > 0 \end{cases} \tag{15}$$

From the above equation (15), the three different probable states are positive, negative or zero. Following which max pooling is applied to the resultant activated two dimensional functions to retain the most prominent pixel image features of the feature map, therefore acquiring sharper image than the preprocessed image. Here, max pooling necessitates scanning over an activated feature map results and at each instance returns the maximum pixel value seized within the filter as a pixels of its own in a new image.

$$MPResults = Max\ [f_{DReLU}(p,q)] \tag{16}$$

In this manner, the prominent features of the feature map are returned as output. In our work, '$2 * 1$' filter with a stride of '2' is initialized. The resulting returned image is referred to as the max pooled characterization of the original preprocessed rice crop image. Next, the prominent features of the feature map are normalized as given below.

$$NR = \frac{u + (MPResults_i - \max(MPResults)) * (v - u)}{\max(MPResults) - \min(MPResults)} \quad (17)$$

Then, with the above (17) obtained normalization results, the equation for the salinity score is formulated as given below.

$$SR = 1.6419 + 0.0733 * NR \quad (18)$$

With the above obtained salinity score (18) values for example sample images provided as input and checking with the Standard Evaluation Score (SES) of salinity at seedling stage, the results are produced accordingly in an accurate manner. The pseudo code representation of Dual Rectified Linear Convolutional Neural prediction-based salinity tolerance in rice at seedling stage is given below.

Input: Dataset 'DS'
Output: precise and accurate prediction results
Step 1: **Initialize** preprocessed Rice crop Images 'PI', '$Bias = 1$', filter '$2 * 1$', stride '2' Step 2: **Begin** Step 3: **For** each Dataset 'DS' with preprocessed Rice crop Images 'PI' Step 4: Evaluate seedling height reduction percentage as given in equation (10) Step 5: Split the resultant seedling height reduction percentage preprocessed rice image with respect to three channels as given in equations (11), (12) and (13) Step 6: Obtain combined feature map as given in equation (14) Step 7: Activate feature map using Dual Rectified Linear Unit as given in equation (15) Step 8: Return prominent features selected via max pooling as given in equation (16) Step 9: Perform normalization as given in equation (17) Step 10: Formulate salinity score value as given in equation (18) Step 11: **If** '$SR = 1$' Step 12: **Then** the sample image is found to be highly tolerant

Step 13: **End if**

Step 14: **If** '$SR = 3$'

Step 15: **Then** the sample image is tolerant

Step 16: **End if**

Step 17: **If** '$SR = 5$'

Step 18: **Then** the sample image is found to be moderately tolerant

Step 19: **End if**

Step 20: **If** '$SR = 7$'

Step 21: **Then** the sample image is found to be sensitive

Step 22: **End if**

Step 23: **If** '$SR = 9$'

Step 24: **Then** the sample image is found to be highly sensitive

Step 25: **End if**

Step 26: **End for**

Step 27: **End**

Algorithm Dual Rectified Linear Convolutional Neural prediction

As given in the above algorithm, preprocessed rice crop Images and seedling height reduction percentage values provided as input, the objective remains in producing the prediction results in an accurate and precise manner. With this objective initially, seedling height reduction percentage for each preprocessed rice crop Images is split into three channels for further processing. Second, combined feature map is obtained with the initialized bias value. Third, the combined feature maps are subjected to Dual Rectified Linear Unit for activation. Finally, prominent features are selected via max pooling and normalization is performed with which the conditionality checking with respect to salinity score value. In this manner, accurate and precise prediction of salinity stress levels at seedling stage is made.

4. Performance evaluation

One of the critical characteristics of designing a significant DL method is evaluating the method's efficiency. Numerous measures are utilized in evaluating the methods efficacy, broadly indicated as performance metrics. These performance metrics permit us in discerning how well the proposed Homomorphic Fourier Integral-based image classification and Dual Rectified

Linear Convolutional (HFI-DRLC) method fits with the provided data and existing methods, optimization strategy for salinity stress at seedling in rice [1] and Genome Wide Association Study (GWAS) and linkage mapping. Some evaluation matrices like, precision, recall, accuracy, mean absolute error (MAE) and prediction time have been evaluated in this experiment to explain the proposed method using Python high-level general-purpose programming language. All of the evaluation criteria related to this study are briefly discussed below using the dataset https://figshare.com/articles/dataset/rice_seedlings_and_weeds/7488830and the real time dataset obtained from ICAR (Central Coastal Agricultural Research Institute, Old Goa, India).

5. Discussion

In this work, the precision, recall, accuracy and F1-score performance metrics are utilized in measuring the performance of the salinity stress level in rice crops at seedling stage. The precision, recall, accuracy evaluation metrics were calculated as follows.

$$Pre = \frac{TP}{TP+FP} \tag{19}$$

$$Rec = \frac{TP}{TP+FN} \tag{20}$$

$$Acc = \frac{TP+TN}{TP+FN+FP+TN} \tag{21}$$

From the above equations (19), (20) and (21), 'TP' refers to the positive sample was predicted as a positive sample (i.e., correctly classified seedling pixels), that is, a correct prediction, 'FP' refers to the negative sample was predicted as a positive sample (i.e., number of pixels misclassified), that is an incorrect prediction, 'FN' denotes the positive sample was predicted as a negative sample, that is an incorrect prediction and 'TN' denotes the negative sample was predicted as a negative sample (i.e., correctly classified background pixels), that is a correct prediction respectively.

The precision rate objective remains in determining how many rice crop sample images predicted to be positive are really positive and is utilized in measuring the correctness for identification of salinity stress level in rice crops at seedling stage based on successful detections. On the other hand, the recall rate objective remains in identifying how many of the really positive rice crop sample images are predicted to be positive and is utilizing in measuring the salinity stress level in rice crops at seedling stage for all targets to be detected.

Finally, the accuracy rate aims in determining the probability of correct prediction among total rice crop sample images respectively. Also to evaluate the estimation performance, mean absolute error (MAE) was evaluated as given below.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}(GT_i - PT_i) \quad (22)$$

From the above equation (22), the mean absolute error value 'MAE' is arrived at based on the difference between the ground truth trait 'GT_i' and the predicted trait 'PT_i' of the corresponding rice crop sample images respectively. Finally, prediction time or the time consumed in salinity stress level analysis in rice crops at seedling stage is mathematically stated as given below.

$$Pred_{time} = \sum_{i=1}^{N} Samples_i * Time(Prediction) \quad (23)$$

From the above equation (23), prediction time '$Pred_{time}$' is measured based on the samples '$Samples_i$' used for analyzing salinity stress level and the actual time consumed in the overall preprocessing and prediction process '$Time(Prediction)$' respectively. It is measured in terms of milliseconds (ms).

5.1 Performance analysis of precision, recall and accuracy

In this section, the performance analysis of precision, recall and accuracy both with and without preprocessing is discussed. As far as rice salinity analysis at seedling stage is concerned, preprocessing plays a major role. This is because of the reason with the application of preprocessing unwanted or irrelevant areas can be eliminated and obtaining significant region of interest. Table 1 list the performance analysis results of accuracy, precision and recall using the proposed HFI-DRLC method and existing methods, optimization strategy for salinity stress at seedling in rice [1], GWAS and linkage mapping [2] respectively (both without and with preprocessing). All the three performance metrics are measured in terms of percentage (%). Higher accuracy, precision and recall ensure the efficiency of the method.

Table 2 Performance evaluation of accuracy, precision and recall (without preprocessing)

Methods	**Without preprocessing**			**With preprocessing**		
	Accuracy (%)	Precision (%)	Recall (%)	Accuracy (%)	Precision (%)	Recall (%)
HFI-DRLC	88.49	92.5	94.38	91.74	95	95.95
Optimization strategy for salinity stress at seedling in rice	85.90	90	93.75	90.90	92.5	94.38
GWAS and linkage mapping	82.01	86	92.97	84.61	88.5	93.65

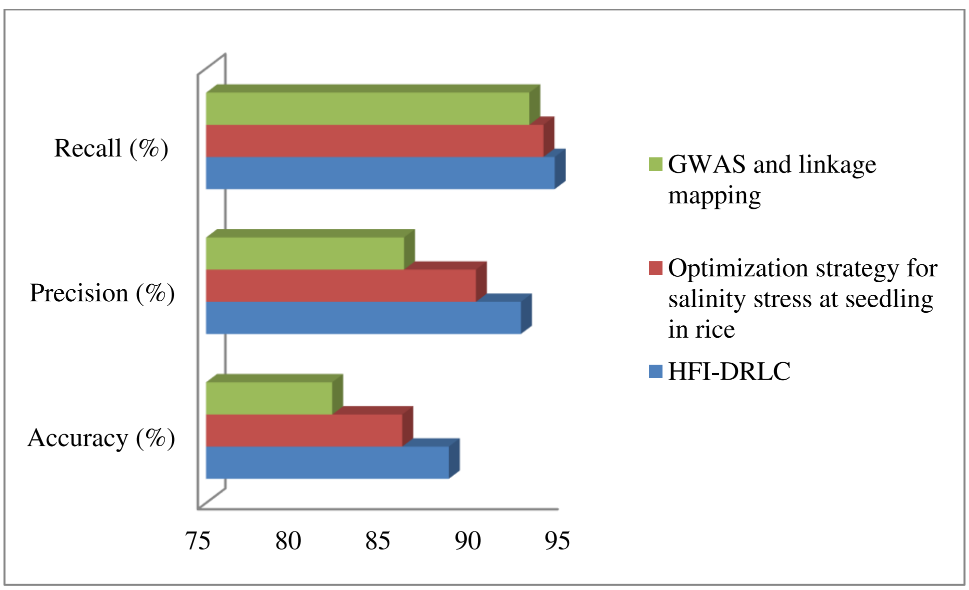


Figure 5 Graphical representations of precision, recall and accuracy

Figure 5 given above shows the graphical representations of precision, recall and accuracy with respect to 200 different sample images. Performance evaluation of three distinct performance metrics was done both with and without preprocessing using the images obtained from both the repository and real time.

Without the application of preprocessing, accuracy, precision and recall rate using the proposed HFI-DRLC method was found to be 88.49%, 92.5% and 94.38% respectively. In case of the existing methods, optimization strategy for salinity stress at seedling in rice [1] and GWAS and linkage mapping [2], the accuracy rate was observed to be 85.90% and 82.01%, precision was found to be 90% and 86% respectively. On the other hand, the accuracy, precision and recall rate when measured after preprocessing using the proposed HFI-DRLC method were found to be 91.74%, 95% and 95.95% respectively. In case of the existing methods, optimization strategy for salinity stress at seedling in rice [1] and GWAS and linkage mapping [2], the accuracy rate was observed to be 90.90% and 84.61%, precision was found to be 92% and 88.5% respectively. From these results it is inferred that the three performance metrics, precision, accuracy and recall rate were observed to be comparatively better using the proposed HFI-DRLC method upon comparison to the existing methods, optimization strategy for salinity stress at seedling in rice [1] and GWAS and linkage mapping [2]. The improvement in terms of precision, accuracy and recall rate was observed owing to the application of Homomorphic Fourier Integral Filter-based Preprocessing algorithm. By applying this algorithm, image enhancement was ensured that in turn not only balanced the contrast but also improved illumination significantly. Initially for each raw side seedling images, product of illumination and reflectance were formulated separately. Second, Fourier Integral function was applied for generating integrated image pixels with the aid of Circular Butterworth high pass filters. On the other end, for acquiring back the preprocessed output image, inverse function was applied that in turn improved the overall precision, recall and accuracy rate.

5.2 Performance analysis of MAE and prediction time

In this section, the performance analysis in terms of MAE and prediction time using the proposed HFI-DRLC method and existing methods, optimization strategy for salinity stress at seedling in rice [1] and GWAS and linkage mapping [2] are detailed. Table 2 list the performance analysis results of prediction time and MAE using the proposed HFI-DRLC method and existing methods, optimization strategy for salinity stress at seedling in rice [1], GWAS and linkage mapping [2] respectively. The prediction time performance metric is measured in terms of milliseconds (ms) whereas the MAE is evaluated in terms of percentage (%). Lower prediction time and MAE ensure the efficiency of the method.

Table 3 Performance evaluations of prediction time and MAE using HFI-DRLC method, optimization strategy for salinity stress at seedling in rice [1] and GWAS and linkage mapping [2]

Methods	Prediction time (ms)	MAE (%)
HFI-DRLC	23.35	2.45
Optimization strategy for salinity stress at seedling in rice	38.25	4.15
GWAS and linkage mapping	45.35	5.85

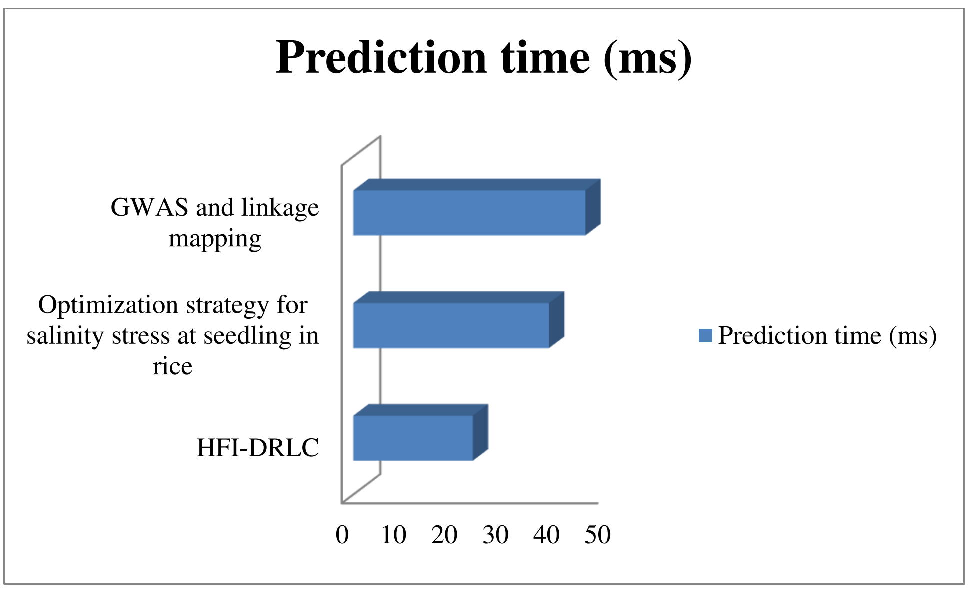


Figure 6 Graphical representation of prediction time

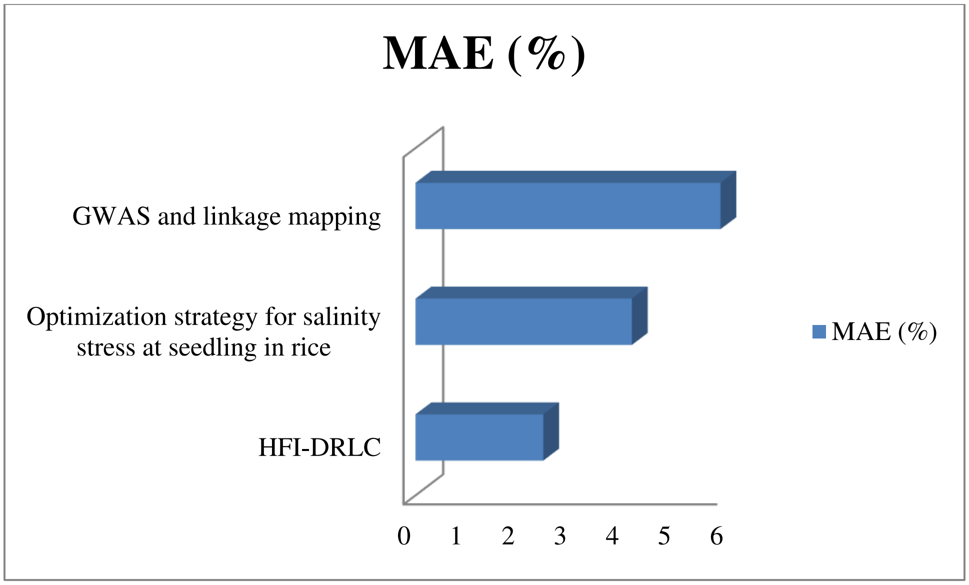


Figure 7 Graphical representation of MAE

Figure 6 and figure 7 given above shows the graphical representation of prediction time and MAE for the three methods, HFI-DRLC, optimization strategy for salinity stress at seedling in rice [1] and GWAS and linkage mapping [2]. For performing fair comparisons between the three methods, same set of 200 sample images(i.e., 100 sample images from repository and 100 sample images from real time)were applied as input for all the three methods. From the above figure 6, the prediction time using the proposed HFI-DRLC method was observed to be comparatively better than [1] and [2]. By applying the Dual Rectified Linear Convolutional Neural prediction algorithm, with each preprocessed rice crop images acquired as input, seedling height reduction percentage were initially obtained. Following which the resultant preprocessed rice crop Images were divided into three distinct channels. Finally, with the initialized bias value, combined feature maps were obtained for further processing. This in turn reduced the prediction time using HFI-DRLC method by 39% and 16% compared to [1] and [2]. Also from the above figure 7, the MAE using HFI-DRLC method was significantly found to be reduced upon comparison to [1] and [2]. The reason was due to the application of Dual Rectified Linear Convolutional Neural Prediction model for measuring salinity tolerance in rice at seedling stage. Here, with the combined feature maps as input were processed and activated using Dual Rectified Linear Unit. With the resultant combined feature maps output images, max pooling and normalization were applied to obtain prominent features.

Finally, to measure the salinity level with the salinity score value and normalized results, conditionality checking was performed to arrive at the final results. This in turn reduced the MAE using HFI-DRLC method by 41% compared to [1] and 29% compared to [2] respectively.

6. Conclusion

Rapid acquisition of contrast-improved and illumination-free preprocessed traits of rice seedlings can assist in comprehending the growth status of rice salinity even at the seedling stage that remains the predominant basis for intelligently agriculture or smart farming. In this study, an image enhancement model that balances field image characteristics like contrast, illumination and key factors for salinity stress level identification in rice crops at seedling stage via field images based on digital images are proposed that could make possible the researchers and learns in making decision in rice crop management techniques. In this work a method called, Homomorphic Fourier Integral-based image classification and Dual Rectified Linear Convolutional (HFI-DRLC) is designed that assists in identifying the salinity stress levels of rice at early seedling stage. The HFI-DRLC method initially performs the preprocessing using the Homomorphic Fourier Integral Filter-based Preprocessing algorithm. The algorithm in turn generates preprocessed results taking into considerations two distinct factors, namely, contrast and illumination for detecting region of interest in an extensive manner. Next, Dual Rectified Linear Convolutional Neural Network prediction model is applied for salinity stress level analysis. Here, Dual Rectified Linear Unit is applied as the activation function to classify according to salinity score. Strong classifier results are hence obtained with comparatively less error. To analyze the performance of HFI-DRLC method significant performance metrics like, precision, recall, accuracy, prediction time and MAE are measured. According to the findings, the HFI-DRLC method achieves higher levels of precision, recall, accuracy with minimum time and error than the other conventional methods.

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