Modelling a Dense Convolutional Model for Crop Yield Prediction Using Kernel Computation

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Abstract

Crop yield prediction is performed based on crop, water, soil and environmental parameters, which is now a potential research field. Machine-learning approaches are extensively utilized for extracting significant crop features. ML approaches help in handling the issues over the crop prediction process. Some essential issues like linear and non-linear data mapping among the crop yielding values and input data need to be analyzed. However, the performance relies on the quality of extracted features. Here, a novel dense convolutional Network model with a kernel is designed to resolve the challenges identified. Based on feature learning, the anticipated model predicts the crop yielding value and linearly maps the crop yielding output with a nominal threshold value. Here, MATLAB 2020a simulator is used and various metrics like precision, accuracy, recall, F1-score, MAPE, RMSE and R^2 value are evaluated with various approaches. The model shows a superior trade-off than other approaches and intends to give better prediction accuracy. The model preserves the original data without disturbing the overall incoming values.

Keywords: Crop yield prediction; Machine learning; Support vector machine; Classification; Feature learning

1. Introduction

Food security depends on accurate crop predictions. Reliable and timely existing agricultural estimates before harvesting are crucial. Researchers used the crop growth approach to predict crop production. The prediction models have two major challenges when predicting agricultural output [1]. First, the calibration process requires several factors, limiting their usefulness. They are generally built for certain locales rely on current occurrences, making it impossible to predict returns elsewhere [2]. Future research addressed yield estimation difficulties using machine learning approaches like SVM, randomization forest (RF), Artificial Neural Networks (ANN) [3], etc. These methods may construct an empirical predictive model employing a predetermined sequence of RSI features without a huge variety of parameters. Handmade features depend on human ingenuity and foreknowledge [4], which aren't necessarily lasting. Such strategies are computationally expensive and can't handle large datasets. All of these issues make crop prediction difficult and provide poor outcomes. With supervised learning, agricultural output predictions use a deep learning model. These methods can extract useful features from raw photos, enabling adaptation to diverse contexts. Cao et al. [5] constructed a stacked auto-encoder (SAE) to retrieve deep spectral information for agricultural production prediction (MSIs). It flattens images into 1-D spectrum vectors that lose geographic info CNNs are used to forecast agricultural production [6]. CNN's accept spatial patchwork as input, which improves performance relative to SAEs [7]. Chen et al. [8] presented two CNN for spatial and spectral information. These techniques have shown that CNNs' deep spatial and spectral properties may develop a generic-based prediction model.

In reality, crop development is a complicated feature influenced by soil qualities, precipitation, etc., which RSIs cannot completely reflect. In such circumstances, CNN-based extensive spectral and spatial feature extraction may not be enough. These crop-related effects are spatially consistent [9]. In this instance, geographic consistency among data sets might assist in forecasting missing variables. Ma et al. [10] found a geographical correlation in

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corn yield modelling techniques for analysing yield monitoring information. Without spatial stability, forecasting models may be erroneous, per Xi et al. [11]. Incorporating organization is to maximize has boosted paddy [13], grains [14], and soybeans [12] prediction. We anticipate that using spatial characteristics and spatial constancy as an aggregate of crop-based traits may enhance growth and yield predictions. Since these two characteristics come from distinct sources, integrating them into the forecasting model is difficult. In this paper, we use hierarchical characteristics to forecast crop production. We offer a new architecture for agricultural production predictions that combines SVM with multi-kernel. To our understanding, we are the first to employ SVM to extract combined spatial-spectral characteristics from MSIs. In [15], a linear regression model is used for final classification, and spatial integrity is considered excess. Our study employs a unique system to extend feature information and spatial coherence inside an activation function and measure prediction uncertainty. Here are the article's primary contributions.

1) A CNN is used to extract spatial features from existing prediction characteristics. Kernel processing can effectively identify strong spatial patterns.

2) The classification model introduces a second "spatial" synthesis kernel function. The new kernel uses deep features and location data to encapsulate deep feature properties and spatial consistency.

3) The yield should prove the method's usefulness. Experiments demonstrated that our technique could accurately estimate crop production.

The work is provided as: Section 2 provides a comprehensive examination of various prevailing works; section 3 provides detailed investigation of the anticipated dense CNN model. The numerical outcomes are discussed in section 4, with the research conclusion in section 5.

2. Related works

Forecasting crop output is a significant subject, and numerous ways have been proposed. For yield prediction, the growth and yield model has been frequently utilized. Previous crop productivity forecasts may be classified into two groups. The initial models forecast crop yielding suing various physiological characteristics like climatic, soil quality, bio-geochemical fluxes, socioeconomic variables, etc. [16]. AquaCrop, CERES-Maize, and APSIM are the most prevalent models. However, these approaches need a wide range of variables are difficult to attain in growing nations. The low geographical generality of these algorithms limits their use [17]. These variations use handcrafted elements like NDVI and EVVI (EVI). It includes a wide range of agricultural forecasting activities. NDVI is used in [18] to forecast US grain output. According to Ji et al. [19], there is a strong correlation between pixel-based MSI-based NDVI and sunflower yield. Similar studies looked at other methods for different types of crops, including linear regression for wheat and corn, the multi-linear projection for the prediction of barley and rice, etc. Following this, Chen et al. [20] introduced spiking CNN architectures for agricultural yield evaluation utilizing NDVI time information. These models are shown to perform better than conventional computational classifications in handling more challenging modelling difficulties. However, given that they are mostly mathematical combinations of a small number of preset bands and are not robust under all conditions, handcrafted elements continue to limit present machine-learning-based methods [21].

Deep learning techniques have already shown great promise in urban planning, land surface classification, and agricultural yield prediction [22]. In contrast to more conventional methods, transfer learning algorithms could extract relevant strong traits from the original image using a theory-originated structure. To predict agricultural output, Tuia et al. [23] presented an SAE for an increase in available features. In this investigation, the pictures were reduced into 1D- matrix that cannot use spatial features. Yeh et al. [24] employed a CNN and LSTM to detect crop-related properties automatically from the provided images for the objective of crop prediction. The findings demonstrate that both the networks exceeded the conventional approach. This limitation was solved using CNN, and the LSTM networks and CNN maintain local spatial characteristics from spatial patches using 2D convolution filters. Numerous researchers have employed CNNs to haul out spatial knowledge in farming yield estimates to achieve this aim [25]. Furthermore, by expanding to other domains utilizing a learning algorithm, the scientists of [26] showed the efficacy of deep learning algorithms in retrieving information. A multi-tier CNN approach is used for rich outcome elements evaluation reported recently by Yang et al. [27] enables the autonomous recovery of spectral properties. The earlier studies supported the advantages of spectral and offered enhanced qualities over handcrafted features [28]. These methods, however, do not fully leverage spatial information due to the limits of 2-D networks [29] – [30]. This research concentrates on modelling an efficient dense network layer for crop yield prediction.

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3. Methodology

Crop production forecasting has been a significant issue, and several types of research have been suggested to improve performance. We explore and use hierarchical characteristics for forecasting in this work. The preliminary step is installing a CNN to haul out spatial information from the input. Several crop dimensionality involved in resolving is used in the CNN to extract features. Second, a kernel based on deep spatial characteristics is used to perform the prediction procedure. The kernel can concurrently retain the deep feature commonalities and the spatial consistency since it can systematically aggregate many representations. We propose a novel dense CNN framework by merging CNN with the kernel, as illustrated in Fig 1. Our dense CNN is divided into two parts: the first is the feature area, which includes the derivation of deep spatial objects from the CNN and the acquisition of crop yield data. Additionally, the model is the kernel and linked on top of the CNN. After the kernel mode, the predictions of the model performance are established. The suggested model can thoroughly dig spatial characteristics from images and produce accurate predictions with feature representation and location information. The dataset is taken from the online available dataset.

3.1. Kernel computation

The kernel space adopts Gaussian Process [31] with the integration of deep feature extracted from the vectors. Here, the general probability description is introduced using Gaussian model and the kernel computation is used for extracting the spatial consistency.

1) Gaussian computation: A general probability (GP) is a group of random variables, each of which has a limited amount and a shared Gaussian distribution [32] – [33]. The distribution of GP is written as, and GP is a non-linear probabilistic model is fully characterized by the average covariance functions.

$$f(x) \sim p\ (m(x), k\ (x, x')) \tag{1}$$

Here, x and x' represents random variables, $m(x)$ represents mean function with the expectation value of $E(f(x)$ and the $k(x, x')$ represents the kernel function with the covariance $cov(f(x), f(x')$. Generally, for simplifying the process, the mean function is taken as 0, and the added noise $\varepsilon \sim p(0, \sigma^2)$, therefore the Gaussian function distribution is nearer to the provided data. For regression evaluation:

$$y = f(x) + \epsilon \tag{2}$$

However, the crop yield distribution y is represented as in Eq. (3):

$$y \sim N(0, L(x, x') + \sigma_n^2\ I_n) \tag{3}$$

Here, I_n specifies the identity matrix. Therefore, with the provided input latent variable set $X = \{x_1, x_2, \dots, x_N\}$ and the yielding process is provided as $\{y_1, y_2, \dots, y_N\}$ with the probability index x_i, which is shown in Eq. (4):

$$P(Y|X, \theta) = \prod_{i=1}^{N} p(y_i|x_i, \theta\ ) \tag{4}$$

$$P(Y|X, \theta) = \frac{1}{(2\pi)^{\frac{DN}{2}}\ |K_Y|^{\frac{D}{2}}} \exp\left(-\frac{1}{2}\ tr\ (K_Y^{-1} y Y^T)\right) \tag{5}$$

Here, K_Y represents the symmetric covariance and matrix $(K_Y)_{ij} = k_y(x_i, x_j)$ is considered for measuring the similarity among x_i and x_j and I_n represents the dimensionality identity matrix.

3.2. Spatial relationship

We may deduce from Eq. (5) that the choice of the kernel function affects how well predictions perform. To capture hierarchical aspects, a composite kernel for the probability inside the multi-kernel architecture is built in

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this section. The dense feature kernel and spatial are the two distinct parts of the used kernel. While in an iteration process, each kernel's weight is discovered.

This section will simulate how far apart the deep features are extracted using CNN. The spatial characteristics extracted from the vector model are utilized to construct the deep feature kernel using the radial basis function (RBF). Let X be the features produced by the vector model, where $X = x_1, x_2, \dots, x_i$. The characteristic kernel may then be stated as:

$$K_{features} = \sigma_f^2 \exp\left[- \frac{||x - x'||_2^2}{2l_f^2}\right] \tag{6}$$

Here, x represents the deep normalized feature during dataset training and x' represents testing data features, $\sigma_f^2, \sigma_s^2, l_f, l_l, and\ l_y$ represent kernel hyper-parameters which are determined as $\theta_1 = \{\theta_l | l = 1, \dots, M\}$.

3.3. Spatial kernel measure

To measure spatial consistency, the Radial bias kernel is constructed, and it is expressed as:

$$K_{spatial} = \sigma_s^2 \exp\left[- \frac{||\Delta_{loc}||_2^2}{2l_s^2}\right] \tag{7}$$

During kernel computation, the similarity is evaluated based on the spatial samples from the data points, where $\Delta_{loc} = |loc - loc'|$ specifies the distance metrics among the training and testing data. The hyper-parameters of the kernel are depicted as $\theta_2 = \{\theta_l | l = 1, \dots, K\}$. This work uses the suggested method to develop a new "spatial" kernel by merging the dense feature module with the spatial and motion kernels. It allows us to combine the data contained within extracted features and the spatial distribution uniformity. We create two similarity vectors for each data provider in these new kernels through the Distance function. One way to describe the new kernel is expressed as follows:

$$K = \sum w_s k_s(x_i, x_j) \tag{8}$$

Where $W_S = \{w_1, w_2\}$ refers to the sub-kernels' weights, because the weights are defined as positive, $w_1 + w_2 = 1$, each kind of feature's inputs may be captured by the optimal weights w_1 and w_2. The $KS = K_{feature}, K_{spatial}$, denotes the deep convolutional and spatial kernels. We specify the characteristic vectors for the new kernel as $\theta_m = \theta_1, \theta_2, w_1, w_2$ since the variables may change for various kernels.

3.4. Prediction process

At last, based on the kernel computation, let Y specifies the training dataset and y' represent the yield is predicted. The distribution of the yield observations Y and the prediction y' is expressed as in Eq. (9):

$$\begin{bmatrix} Y \\ y' \end{bmatrix} \sim \left(0, \begin{bmatrix} (XK, X) + \sigma_n^2 I_n & K(X, x') \\ K(x', X) & k(x', x') \end{bmatrix}\right) \tag{9}$$

Here, $K(X, x') = K(x', X)^T$ specifies the $(n * 1)$ order covariance matrix among the prediction variables x' and training set X. Based on these distribution, probability distribution function for yield prediction y':

$$P(y'|x', X, Y) \sim N(E[y'], cov(y')) \tag{10}$$

Here,

$$E[y'] = K(x', X)[K(X, X) + \sigma_n^2 I_n]^{-1} y \tag{11}$$

and

$$cov(y') = k(x', x') - K(x', X) * [K(X, X) + \sigma_n^2 I_n]^{-1} K(X, x') \tag{12}$$

Here, this work adopts $E[y']$ represents the final prediction outcome, $cov(y')$ represents the uncertainty measure. Figure 1 depicts the kernel-based dense network model.

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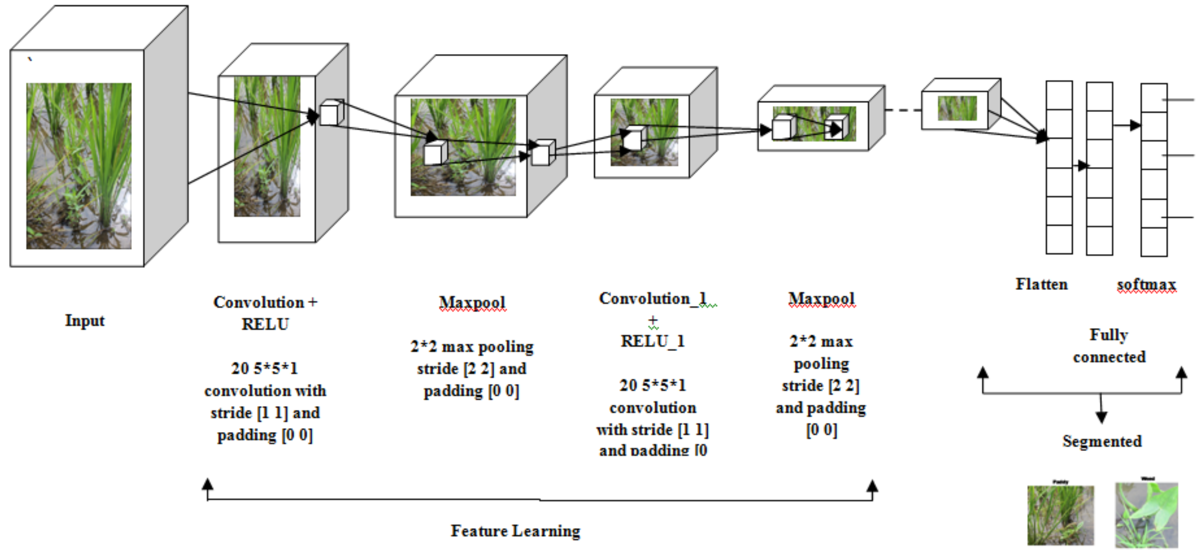

Figure 1. Dense CNN-based crop yield prediction

4. Configuration

All the accompanying tests are carried out on a 64-bit Intel Core i7 running at 3.20 GHz RAM are available. Under CUDA version 9.0.176, only one GPU is used. The suggested model is contrasted with the popular crop yield prediction techniques to verify its efficacy. The following is a summary of them. The most popular metrics for assessing correlation coefficients, RMSE, R^2, and MAPE, among the actual yield and anticipated yield are used to assess the crop yield prediction system efficiency. These metrics may be described as follows:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(p_i - y_i)^2} \tag{13}$$

$$R^2 = 1 - \sum_{i=1}^{m}(p_i - y_i)^2 / \sum_{i=1}^{m}(p_i - \bar{y})^2 \tag{14}$$

$$MAPE = \frac{100\%}{m}\sum_{i=1}^{m}\left|\frac{p_i - y_i}{p_i}\right| \tag{15}$$

Where m is the quantity of forecasting data points, y_i and p_i are the label and projecting output, and y is the median outcome.

Table 1: Comparative analysis

Method	**RMSE**	$\boldsymbol{R^2}$	**MAPE**
LSTM-GP	0.95	0.65	18.33
2D-GP	0.94	0.67	19.05
3D-GP	0.78	0.77	17.35
LSTM-MK	0.92	0.68	17.65
2D-MK	0.84	0.73	15.86
3D-SGP	0.76	0.78	14.58
Dense CNN	**0.70**	**0.80**	**14.35**

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4.1. Analysis

The application of the dense CNN to specifically spatial characteristics is one of the study's achievements. In contrast to the 1D-CNN, the 2D convolution layers' third aspect allows for exploring spatial correlations to the kernels. We change the kernel's width while leaving all other level positions constant to investigate the impact of the kernel size. Here, we test out various kernel widths set between 1 and 5. Note that the depth structure = 1 is identical to the 2-D CNN. Figure 2 displays the experimental outcomes of the dense CNN with various kernel widths. Among the entire kernel, depth = 3 is shown to get the best outcomes. Since depth = 1 is equivalent to a dense CNN, which cannot completely dig spatial characteristics, the poorest results are anticipated. The newly developed "spatial" kernel combines two kernels, and the optimized weights of each kernel will directly provide a ranking priority to every kind of information. By altering the weight of the deep feature kernel w_1 to emphasize the contributions of the deep vector features and spatial consistency information which demonstrate how each feature has affected the outcome.

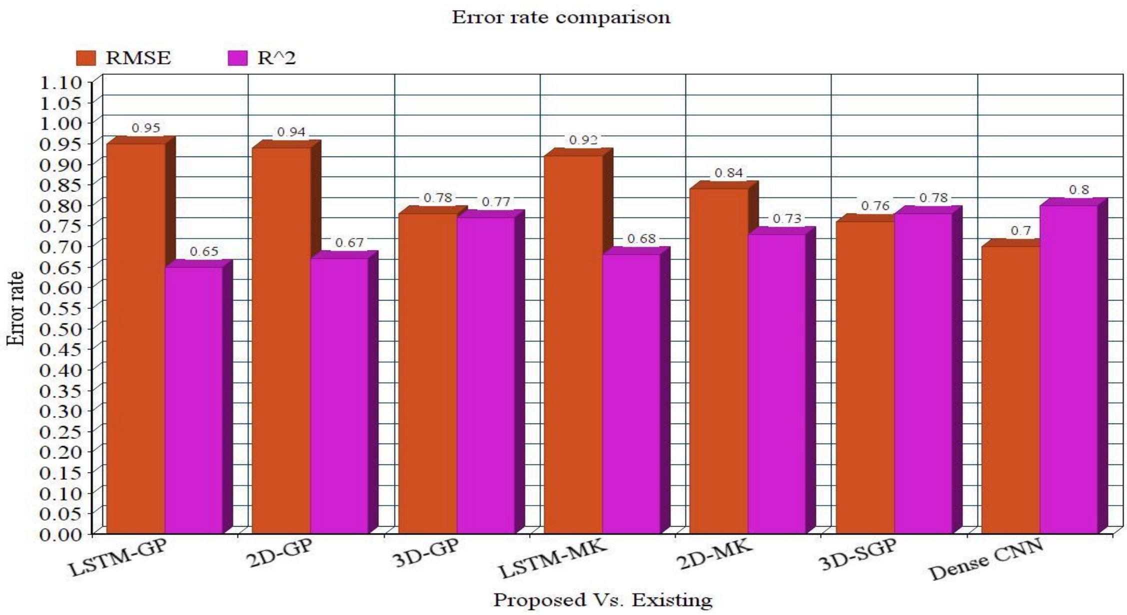

Figure 2. Error rate evaluation

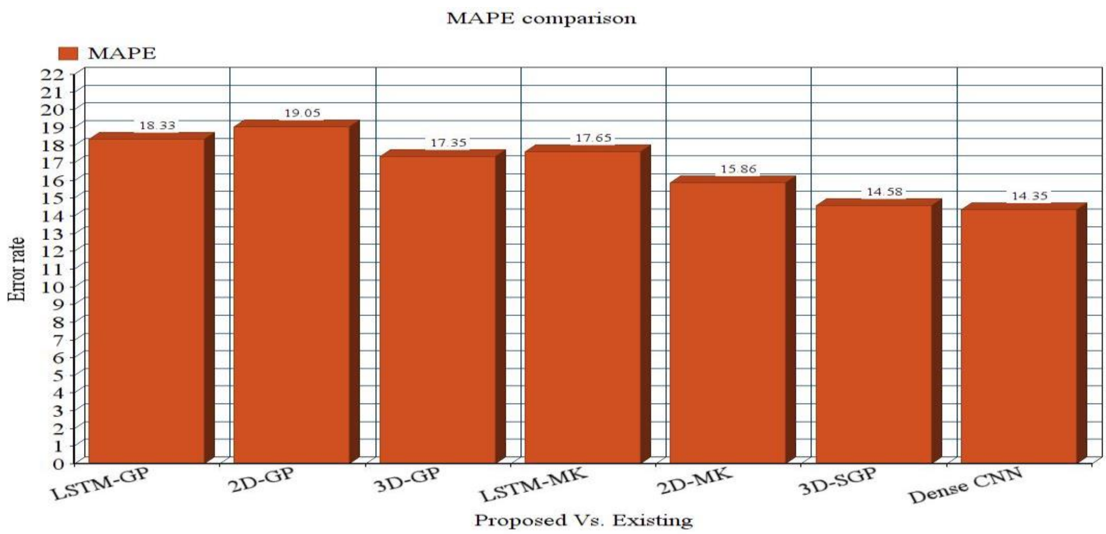

Figure 3. MAPE comparison

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From Figure 3, it is clear that the optimized weights with $w_1 = 0.7$ and $w_2 = 0.3$ obtain the greatest performance, demonstrating the importance of texture networks in crop yield prediction. The RMSE seems to rise when the value of w1 decreases continually. With a weighting of 0.3, the spatial coherence characteristic also contributes significantly to crop production prediction. The examination of w_i can assist in highlighting the contributions made by each feature and provide further guidance for selecting features in yield prediction.

4.3. Numerical results

The anticipated deep network model is executed in the MATLAB 2020a simulation environment. The outcomes are validated with recall, accuracy, precision, and F-measure. The deep network model is known as an 'inducer'. For deep classification, inducers are used for provisioning the system performance. It provides superior outcomes compared to other techniques. Next, the classifiers are merged with CNN blocks and R50, where outcomes are attained with superior predictive function. Here, the open online dataset is considered, and evaluation is done with various metrics and expressed in Eq. (16) - Eq. (9):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{16}$$

$$Precision = \frac{TP}{TP + FP} \tag{17}$$

$$Recall = \frac{TP}{TP + FN} \tag{18}$$

$$F - measure = \frac{2\,(TP)}{2\,((TP) + (FN))} \tag{19}$$

True Positive (TP) – the dense CNN model intends to identify the right features as appropriate ones;

True Negative (TN) – the dense CNN model intends to identify the incorrect features as wrong ones;

False Positive (FP) – the dense CNN model intends to predict the incorrect features as the right one;

False Negative (FN) – the dense CNN model intends to predict the right features as wrong ones;

The images are resized and converted to black and white before being used as input for the model. During training, we choose a batch size, and the process runs for 100 cycles (epochs). To evaluate the model, we run it ten times to get an average result. Batch normalization helps speed up training and improve performance before the data moves to the next layer. It also enhances the training process. The results show that the model performs well during testing and training, effectively managing overfitting. Dropout techniques are used to make the model more general. The loss function decreases over time during both testing and training. When stable, the training loss is zero, and the testing loss is close to zero, indicating good generalization and no overfitting or under fitting. Accuracy increases with each iteration, showing stability as the gap between testing and training accuracy narrows, suggesting the model handles unknown data well. The experiment was conducted on a computer with 8GB of memory. The framework used is the Deep Learning toolbox from MATLAB 2020a with a pre-trained CNN model. Some parameters include a dropout probability of 0.5 for fully connected layers, adaptive gradient descent optimization with a batch size of 64, 20 maximum epochs, an initial learning rate of 0.01, and a learning rate reduction to 0.1 of previous epochs.

Table 2: Performance metrics comparison

Metrics	**ResNet**	**GoogleNet+ ResNet**	**R-50**	**DenseNet**	**Dense CNN model**
Precision	76%	88%	88%	89%	96%
Recall	62%	89%	87%	83%	93%
F-measure	66%	90%	87%	82%	91%
Accuracy	67%	89%	88%	83%	94%

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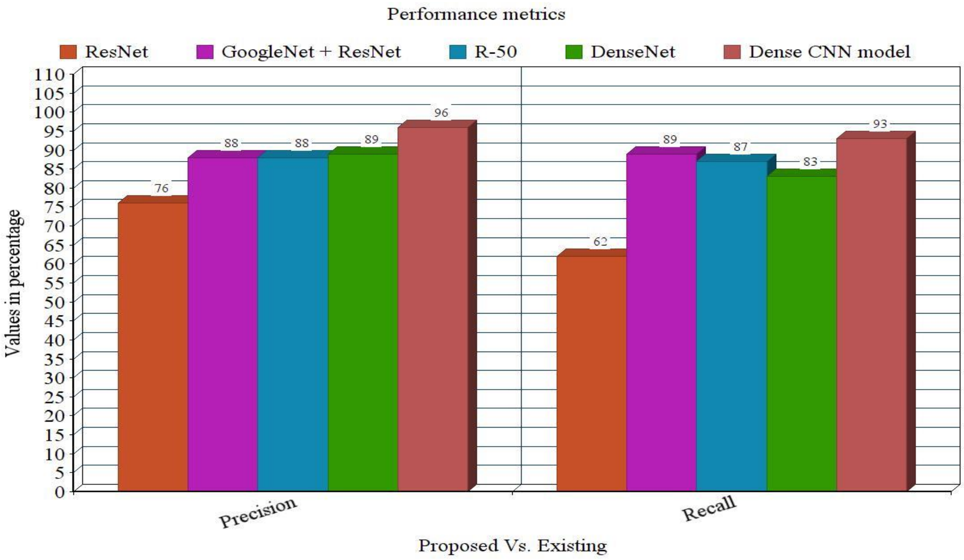

Figure 4. Precision and recall comparison

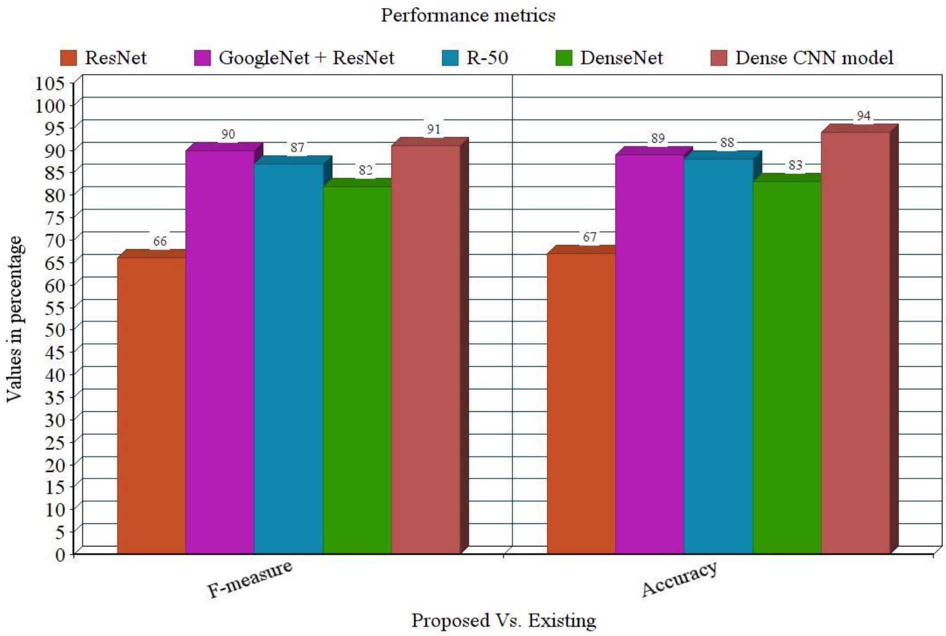

Figure 5. F-measure and accuracy comparison

Table 2 compares various performance metrics. The precision of proposed dense CNN is 95% which is 20%, 8%, 8% and 7% higher than ResNet, GoogleNet+ResNet, R-50 and DenseNet. The recall of the proposed dense CNN is 92% which is 32%, 4%, 8% and 10% superior to other approaches. The F-measure of the anticipated dense CNN is 90% which is 25%, 1%, 4% and 9% superior to other approaches. Finally, the accuracy of the anticipated model is 93% which is 25%, 5%, 4.5% and 11% superior to other approaches. Thus, it is proven that the model works well with the various existing approaches and gives better results (See Figure 4 and 5).

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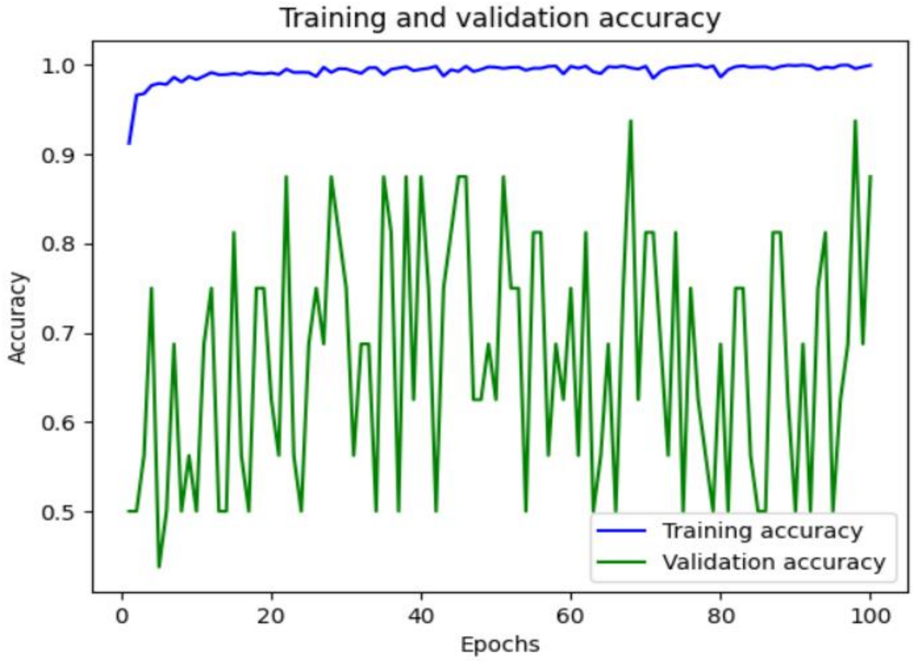

Figure 6. Training and validation accuracy

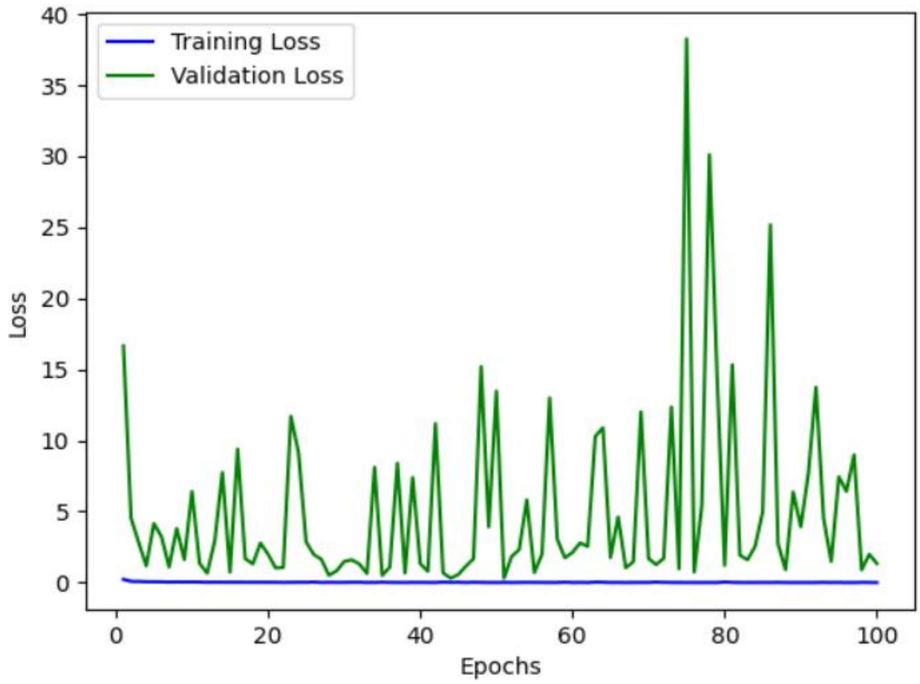

Figure 7. Training and validation loss

The scaling factor is set as 1.2, where the horizontal and vertical shifts transform the images by 20 pixels rightward and downward. For rotation purposes, the random rotation angle ranges from $0 \rightarrow 360$ degrees. The horizontal and vertical flips produce novel images by horizontal and vertical flipping. In the anticipated model, the scaling rate is set as 1.2 as the scaling provides superior trained R-50 among the conventional methods and provides superior sensitivity. The probable explanation is attained with the fine-grained structural model with scaled images that are more recognizable and clear. Moreover, horizontal and vertical flip offers superior specificity and remains

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to be explored. Nonetheless, the proposed method shows better prediction accuracy via specificity and sensitivity are enhanced. From Figure 6 and 7, the training accuracy and training loss with validation accuracy and loss is computed for 100 epochs. The model gives better training accuracy and lesser training loss. The validation is done for the anticipated model; the average validation accuracy is higher and shows a lesser loss. Thus, based on the experimentation, the significance of the model is highlighted.

4.4. Uncertainty measure

One of the major components of the forecasting issue in real-world applications is providing the outcomes' amount of uncertainty. A natural method for estimating uncertainty is made possible by the dense CNN capacity to learn the likelihood function of the predictions. In this section, the randomness in the crop yield forecast has been estimated using the 95 percent ensure that the information computed using the dense CNN model.

5. Conclusion

In this work, hierarchical crop characteristics are used to estimate crop production. In extracting spatial characteristics from raw images, we first use the superiority of the dense CNN. We apply a forecasting system that combines the deep characteristics with spatial regularity features across data points to account for the variables far beyond. Additionally, the kernel-based technique incorporates the prediction system. Numerous experimental findings show that the proposed approach performed better than other standard and machine learning-based approaches and generated more discriminative image features, indicating its potential use in various prediction applications. In future studies, we can include additional crop-based characteristics with the kernel technique. Additionally, our approach is generalizable to crop types other than corn for yield estimation.

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