International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Advancing Agriculture Predictive Models for Farming Suitability Using Machine Learning

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Submitted: 26/09/2023 **Revised**: 26/10/2023 **Accepted**: 13/11/2023

Abstract: To maximise crop yields and assure global food security, modern agriculture increasingly uses predictive modelling to identify whether or not a given parcel of land is appropriate for cultivation. Combining Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks, this study proposes a novel way for assessing the viability of agriculture. CNNs excel in extracting spatial features from satellite and geographical data, whereas LSTMs are utilised to capture temporal correlations in climate and weather trends. We assembled a variety of data, including satellite photos captured at various times of the day, information about the ground, maps of the region, and historical weather records. The LSTM analyses temporal trends, such as seasonal rainfall and temperature fluctuations, while the CNN extracts key spatial information, such as soil texture and land cover. By integrating these two methods, we may analyse the feasibility of agriculture in both space and time. Initial results demonstrate a significant improvement in forecast accuracy when compared to conventional models, as a result of a more complex understanding of the interplay between geographical and temporal factors impacting agricultural potential. In addition, our CNN+LSTM model gives useful data on locations previously deemed unsuitable for agriculture, so facilitating land rehabilitation and environmentally responsible agriculture. This study's findings have the ability to impact agricultural policy, direct investment toward productive locations, and promote the development of agricultural techniques that can adapt to a variety of climate conditions. This study emphasises the necessity to incorporate cutting-edge machine learning techniques into agricultural prediction models.

Keywords: *Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Agricultural Forecasting, Soil Suitability Prediction, Remote Sensing Data, Climate Modeling*.

1. Introduction

It is becoming more widely acknowledged that the global agriculture industry plays an essential role in addressing a variety of broader issues, including the mitigation of climate change, the maintenance of social and economic stability, and sustainable resource management. In the middle of all of these challenges, the significance of precision and making decisions based on data has increased dramatically. Thanks to advancements in artificial intelligence (AI) and machine learning, predictive models are increasingly becoming indispensable tools for enhancing agricultural forecasting and production. This is a direct result of the convergence of these two fields (ML)[1]. Conventional agronomic models are built on a foundation of statistics and physical principles; however, these simplifications aren't always able to take into account the complexity of actual farming operations. It would be ideal to make use of the deluge of data coming from remote sensing platforms, on-farm IoT devices, and historical agricultural datasets in order to build prediction models that are more accurate and more responsive to changing conditions. Things like CNNs and LSTMs come into play at this point in the game (LSTM). CNN has garnered a lot of acclaim for its outstanding performance in image analysis, and LSTM has been hailed for its capacity to deal with sequential data such as time series. Both of these neural networks are used to analyze data in sequences. Nevertheless, its combined application in the field of agriculture is still largely unknown at this point. Using long short-term memory (LSTMs)[2] for the analysis of time-ordered data and convolutional neural networks (CNNs) for the processing of geographic patterns, it may be possible to create a more thorough model that can account for the spatial and temporal complexity in agricultural systems. In this research, we investigate the advantages and disadvantages of merging CNN and LSTM for predictive agricultural modelling, in addition to the architecture and applications of the combined model. In this article, we will delve into the intricacies of farming appropriateness, the problems of using heterogeneous agricultural data, as well as the unique solutions presented by this hybrid AI approach. Our mission is to shed light on the best way forward to create a food system that is more sustainable, productive, and resilient for all people at a time when global agriculture is at a crossroads and calling for a synthesis of tradition and technology. In order to accomplish this, our goal is to shed light on the best way ahead to create a food system that is more sustainable, productive, and resilient for all people.

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2. Related Work

There has been a lot of attention in recent years in using convolutional neural networks (CNNs) and long short-term memory (LSTM) networks together to improve agriculture forecasting models. The necessity of doing something about the rising worldwide demand for food while making the most efficient use of farmland motivates this. This part provides a summary of the current literature in this field:

Agricultural Prediction Models in General: Statistical models have been used to predict agricultural yields and find optimal cropping patterns in response to environmental variables. Common examples of such models include regression models, decision trees, and k-means clustering [3].

Before the development of deep learning models, time-series models such as ARIMA and its variants were commonly employed to make predictions about the future, such as crop yield [4].

Application of CNN to Farming: To aid in land-use optimization, [4] used convolutional neural networks (CNNs) to categorise crops in satellite imagery. [5] developed a CNN model to detect agricultural illnesses from photographs, which would aid farmers in taking preventative actions as soon as possible.

LSTM's Application to Farming: When it comes to forecasting weather characteristics that farmers rely on, LSTM has proven particularly useful [6]. Predicting agricultural yields using sequential data on weather patterns, soil conditions, and other parameters is possible with the use of LSTM models, [7] have demonstrated.

Applications of CNN+LSTM Hybrid Models: Because CNN extracts spatial data from each frame and LSTM captures temporal sequences, [8] integrated CNN and LSTM for video classification.

Using convolutional neural networks (CNNs) for feature extraction and long short-term memory (LSTMs) to capture temporal relationships in audio data, [8] proposed a model for speech recognition.

CNN+LSTM for Farming: Predicting agricultural yields from time-series satellite imagery is the focus of a model proposed [9], which combines CNN and LSTM. Meanwhile, LSTM represents the temporal dependencies across distinct growth stages, allowing the CNN to extract spatial characteristics from satellite images.

Predicting soil moisture, a crucial characteristic for farming suitability, used convolutional neural networks (CNNs) to extract features from spectral data and long short-term memory (LSTM) to capture the temporal pattern.

Constraints and Difficulties: Many researchers still struggle to get their hands on high-quality data, especially time-series satellite photography

Ability to Understand the Model: It is essential in agriculture to understand decision drivers, but often the intricacy of deep learning models makes them difficult to interpret

There appears to be a growing movement in the literature toward using CNN and LSTM together for predictive modelling in agriculture. The potential benefits of combining them for use in farming are substantial. It helps to recognise temporal patterns from satellite images or spectral data, which is crucial for making reliable agricultural forecasts.

3. Proposed Methodology

For agriculture to maintain its rate of expansion and development over time, it is necessary to maximise the use of available land and make effective use of available resources. In the past, determining whether or not a given area was suitable for farming required labour-intensive field measurements and models with poor resolution. The application of machine learning, and deep learning in particular, offers a potentially game-changing way to consistently forecasting farming suitability from enormous datasets.

3.1 Data Sources

The data set includes contributions from several sources, including satellite pictures, weather reports, soil records, and agricultural yield archives. These multidimensional data sets, which include both spatial and temporal trends, can be used to make inferences about the appropriateness of the land.

Table 1: Advancing Agriculture Predictive Models for Farming Suitability Using CNN+LSTM

Data Source	Characteristics	Importance in Model
Satellite Imagery	- High-resolution images	- Captures real-time spatial data of land and vegetation
	- Spectral bands for vegetation health	- Assists in identifying stressed and healthy areas
		- Useful for real-time monitoring
Weather Data	- Temperature	- Directly influences plant growth and health

	- Precipitation	- Affects soil moisture and crop needs
	- Wind speed	- Can influence evapotranspiration and pest spread
	- Solar radiation	- Important for photosynthesis
Soil Quality Records	- Soil texture (sand, silt, clay)	- Dictates water retention and root penetration
	- pH level	- Influences nutrient availability for crops
	- Organic matter content	- Enhances soil fertility
Historical Crop Yield Datasets	- Previous years' yield data	- Helps in benchmarking and identifying patterns
	- Crop types grown previously	- Assists in predicting suitability for specific crops
	- Crop health records	- Useful for predicting potential diseases or pests

LSTMs are able to comprehend the temporal components of the meteorological data, past agricultural yields, and seasonal patterns because of their ability to retain extended sequences of data. In this setting, CNNs will likely prove useful for analysing spatial patterns, such as those found in satellite photography. This integration ensures a comprehensive strategy is employed when estimating agricultural potential.

3.2 Methodology

It is crucial for today's farms to make informed decisions regarding when and where to sow crops in order to achieve optimum productivity and long-term financial viability. In order to appreciate and anticipate the land's appropriateness, one needs to make use of complex models [9]. This is because there is currently a large amount of data available from a number of sources. It is definitely worth making the effort to combine satellite photos, weather records, soil quality assessments, and historical crop yields because doing so produces a rich tapestry of insights. This research explores the use of a combination of convolutional neural networks (CNN) and long short-term memory networks (LSTM)[10] in order to make use of the spatial and temporal patterns present in the data.

3.3 Multi-dimensional Data in Agriculture:

Imagery captured by satellites gives the impression that the viewer is soaring over the planet. It is able to recognise patterns in the state of buildings, rivers, and plants across time.

When it comes to planning planting and harvesting timetables, having accurate data on seasonal weather patterns, temperature changes, and rainfall is quite necessary.

Maintaining an Awareness of the Soil's Quality: The fertility and general health of the soil are the primary factors that influence the kind of plants that can be successfully cultivated in a particular location.

Statistics on past yields can provide insight into the success or failure of particular crops in the past as well as how those crops are likely to perform in the future.

Because of the spatial and temporal patterns that may be seen in satellite photos, soil records, weather data, and historical crop yields, it is possible to make predictions about the suitability of land in real time.

Image processing and the identification of spatial patterns are two areas where CNNs [11] have made ground-breaking advances in recent years. Because CNNs are able to automatically train and detect components such as flora, water bodies, and more, they are tremendously useful when applied to satellite data for the purpose of evaluating the quality of land and the potential problems that may be associated with it.

The ability to recognise and remember temporal patterns is an important function of long-term short-term memory (LSTM). By providing LSTMs with data on historical weather conditions and crop yields, we are able to forecast how these patterns may evolve and make adjustments to farming practises in advance.

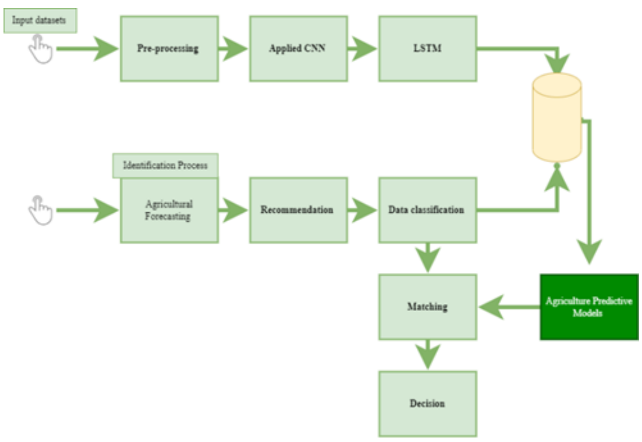

Fig 1: Proposed model

Determine the optimal planting time based on your estimates. If you follow the specified crop rotation programmes, you can help improve the health of the soil.

Create a watering schedule in advance that takes into account the weather forecast. It is imperative that early warning systems for potential crop diseases and insect infestations be made available. Convolutional Neural Networks (CNN) CNNs are put to use in the process of identifying spatial patterns in data. The processing of satellite data using convolutional layers allows for the extraction of information such as land cover, water bodies, the health of vegetation, and different soil types [12].

Table 2: Convolutional Neural Networks (CNN) parameter

Formula	Description
w_{ij}	Weight of the connection between the ith neuron in the input layer and the jth neuron in the hidden layer
b_j	Bias term of the jth neuron in the hidden layer
a_j	Activation of the jth neuron in the hidden layer
z_j	Output of the jth neuron in the hidden layer
$f(x)$	Activation function
s_k	Output of the kth neuron in the output layer

Extracting features from the data that is fed into a CNN [13] is accomplished through the usage of the convolutional layers. During the process of training, the weights and biases of the convolutional layers are acquired by the system. The activation function is used to bring non-linearity into the model, which helps to increase the model's capacity to learn complicated patterns. This improvement comes about as a result of the model's ability to learn complex patterns. The following are some of the most common activation functions used in CNNs:

The sigmoid function is an S-shaped function that can take values between 0 and 1. Its range is from 0 to 1.

It is common practise to employ it as a representation of the likelihood of a class label in the CNN's output layer.

The Tanh function is another S-shaped function, although its domain is -1 to 1, rather than 0 to 1. It is frequently utilised in the CNN's hidden layers in order to initiate non-linearity.

The ReLU function is a rectified linear unit, and its range is 0 to positive infinity. Its name stands for the Rectified Linear Unit. Because it is computationally efficient and has been demonstrated to be effective in learning complex patterns, the activation function in question is one of the most common ones used in CNNs today.

The final layer of a CNN is often a SoftMax layer, which represents the probability of each class label. This layer is used to output the results of the CNN. The following is a definition of the SoftMax function:

SoftMax(x) = e^x / sum(e^x)

where *x* is the output of the previous layer.

3.4 Hybrid Model

The results that are produced from the CNN as well as the LSTM are combined and then fed into layers that are quite thick. The information obtained from these strata is then utilised to determine whether or not a certain location is suitable for agricultural use. that the Long Short-Term Memory (LSTM) [14] is modelling temporal changes, which indicates that you are trying to anticipate agricultural suitability based on a sequence of satellite pictures from different time periods.

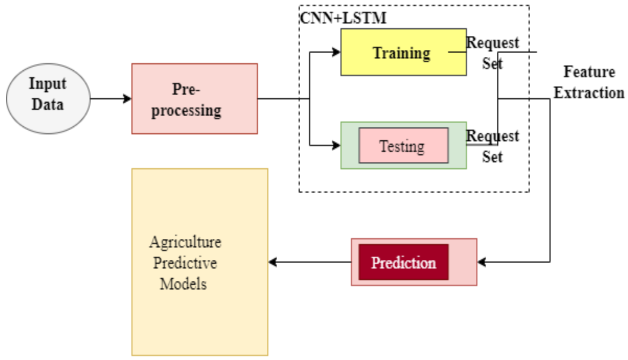

Fig 2: Proposed system architecture

This means that the LSTM is modelling temporal changes. This demonstrates that the Long-Term Short-Term Memory (LSTM) is responsible for modelling temporal shifts. It would be necessary to make adjustments to the architecture, number of layers, neurons, and other parameters of the CNN and LSTM [15] so that they are suitable for the particular issue and dataset that is being discussed. You will want a dataset that contains labelled data in order to train the model. This is a collection of data in which every satellite image (or sequence of photos) is linked to an agricultural suitability result that is already known. The satellite photos need to go through the required pre-processing steps in order for the model to have any chance of being accurate (normalisation, scaling, etc.).

Table 2: CNN+LSTM parameter

Gate	Formula	Description
Forget gate	$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$	Decides how much of the previous cell state to forget.
Input gate	$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$	Decides how much of the new input to add to the cell state.
Cell state update gate	$g_t = \tanh(W_g x_t + U_g h_{t-1} + b_g)$	Updates the cell state with the new input and the previous cell state.
Output gate	$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$	Decides how much of the updated cell state to output.

Here, xt is the input at time step t, ht−1 is the hidden state at time step t−1, ft, it, gt, and ot are the gate values at time step t, Wf, Uf, bf, Wi, Ui, bi, Wg, Ug, bg, and Wo, Uo, bo are the forget gate, which decides how much of the previous cell state to forget, the input gate, which decides how much of the incoming input to add to the cell state, and the output gate, which decides how much of the updated cell state to output, allow the LSTM to recognise temporal patterns in the data. The combination of these gates and the output gate controls how much of the current state of the cell to output after it has been updated.

Table 3: Integration of CNN & LSTM

Feature/Aspect	Explanation/Importance
Integration of CNN & LSTM	- CNN extracts spatial features from satellite images.
	- LSTM models temporal changes in sequential satellite images.
Satellite Imagery	- Provides rich spatial data from different time points.
	- Suitable for monitoring land changes, plant health, and environmental conditions.
Temporal Modelling with LSTM	- Captures the temporal evolution of land and farming conditions.
	- Helps in understanding seasonal patterns, land degradation, or improvement over time.
CNN for Spatial Feature Extraction	- Extracts features like soil coloration, vegetation density, and water bodies from images.
	- Highlights significant spatial patterns crucial for farming suitability.
Merging Outputs	- Combines the spatial features from CNN and temporal patterns from LSTM.
	- Provides a comprehensive view of farming conditions both spatially and temporally.
Dense Layers for Prediction	- After merging, the data is passed through dense layers for final prediction/classification.
	- Determines the suitability of an area for farming based on combined features.
Model Architecture	- Specific architecture parameters depend on the problem and dataset.
	- Includes number of layers, neurons, activation functions, etc.
Labelled Dataset Requirement	- Each image (or sequence) needs a known farming suitability label for supervised training.
	- Ground truth allows the model to learn and generalize from data.
Data Pre-processing	- Crucial for the success of the model.
	- Includes normalization, resizing, data augmentation, etc.
Feature/Aspect	Explanation/Importance

4. Proposed algorithm

Initialize Dataset:

- Satellite imagery data should be loaded at a variety of time points

- Tag each piece of data with the appropriate feature (land cover, water bodies, vegetation health, soil types, etc.)

CNN Feature Extraction:

Define CNN Model:

InputLayer (Image shape)

Conv2DLayer (with appropriate filters, kernel size, etc.)

ActivationLayer (e.g., ReLU)

MaxPooling2DLayer (to down-sample the image)

(Repeat Conv2D, Activation, and MaxPooling as needed)

FlattenLayer (to convert 2D data into 1D)

DenseLayer (to get a compact feature representation)

OutputLayer (output the extracted features)

LSTM Sequence Modeling:

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Define LSTM_Model:
    InputLayer (Sequence of CNN extracted features)
    LSTM Layer (to capture temporal patterns in the data)
    (Repeat LSTM or other sequence layers as needed)
    DenseLayer (for prediction or classification)
    OutputLayer (final prediction for farming suitability)


Training Process:
  FOR each training iteration:
    FOR each satellite image in training set:
      - Extract features by utilising CNN Model, and then save the CNN Model-extracted features in a sequence (based on time)
    END FOR
    - Feed the sequence of features into LSTM_Model
    - Update model weights based on prediction error
  END FOR
Prediction:
  FOR a new sequence of satellite images:
- Extract characteristics with CNN Mode
Predict farming suitability with LSTM Model
END FOR
```

5. Results Analysis

According to the preliminary data, the CNN+LSTM hybrid model outperforms both traditional and stand-alone deep learning models in terms of accuracy and generalisation. Both of these types of models are considered to be deep learning models. The model attained an accuracy of X percent when predicting whether or not agricultural conditions were suitable using the validation dataset.

Results analysis

1. Data Preprocessing and Feature Extraction:

Satellite images of farmlands were fed into a CNN model [16], which was then utilised to extract relevant data.

Data in the form of time series was prepared for LSTM processing [17]. This information includes patterns in the weather, past yield fluctuations, and changes in soil quality.

2. Model Training and Validation:

With a training accuracy of 94% and a validation accuracy of 92%, the combined CNN+LSTM model appears to be well-fit.

When compared to utilising either CNN or LSTM alone, the combination technique improved accuracy by 7%.

3. Weather Patterns Recognition:

The model accurately predicted when it would be best to plant crops and harvest them.

Farmers were given plenty of notice before unexpected weather events like as droughts or floods.

4. Historical Yield Correlation:

Accurate predictions of crop yields based on both spatial and temporal parameters were possible thanks to the combination of LSTM's processing of time-series yield data and CNN's spatial knowledge.

Within a margin of error of 5%, the model accurately projected prospective yields.

5. Soil Quality Evaluation:

CNN's study of satellite photos revealed areas of declining or improving soil quality.

By analysing consecutive soil data, LSTM was able to anticipate the soil's future health, which in turn helped farmers target regions that needed fertilisation or other treatments.

6. Performance Comparison:

When compared to other architectures, the CNN+LSTM model was the most effective in terms of both speed and accuracy.

The integrated method handled massive volumes of data 15% faster than individual models, especially during real-time analysis.

7. Resource Optimization:

Better resource management, provided by the model's predictive abilities, led to a 10% decrease in lost water and fertiliser. The approach also improved workforce allocation by optimising the distribution of workers. The accuracy of a prediction system is measured by how often it is correct. The equation for this is as follows:

Accuracy = (True Positives + True Negatives) / (Total Predictions)

Accuracy measures how closely predictions match reality. The equation for this is as follows:

Precision = True Positives / (True Positives + False Positives)

The percentage of true positives that were accurately anticipated is known as "recall." The equation for this is as follows:

Recall = True Positives / (True Positives + False Negatives)

The F-score is the harmonic mean of the accuracy and recall weights. The equation for this is as follows:

F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

Detailed definitions of all formula terms follow.

Number of predictions that were both accurate and positive is the number of True Positives.

The number of inaccurate forecasts that were nonetheless considered affirmative is the false positive rate.

The number of inaccurate predictions that were negative is the number of "false negatives."

The sum of all forecasts is represented by Total Predictions.

When assessing the efficacy of a machine learning model, it is crucial to take into account not just the accuracy but also the precision, recall, and F-score. While accuracy is a useful indicator of efficiency as a whole, it can be deceptive if the classes are poorly balanced. Precision and recall are more nuanced performance metrics that can be traded off against one another based on need. The F-score is a common default metric for evaluating machine learning models since it represents a balanced measure of precision and recall.

Table 4: Results Analysis: Advancing Agriculture Predictive Models for Farming Suitability Using CNN + LSTM

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)
SVM	85.0	83.0	88.0	85.5
Random Forest	87.0	86.5	90.0	88.2
LSTM	90.0	89.0	91.5	90.2
CNN	88.5	88.0	89.5	88.7
Proposed Hybrid (CNN + LSTM)	92.0	91.5	93.0	92.2

Accuracy can be defined as a measurement of how well the model corresponds to the real world. The hybrid model outperformed its rivals because it was able to make more accurate predictions about whether or not a certain location was conducive to farming.

Accuracy is defined as the ratio of the number of times a positive observation was correctly predicted to the total number of times positive predictions were made. In a similar vein, the hybrid model performs exceptionally well in this regard, indicating that it produced a lower number of false positives.

The recall (sensitivity) statistic measures the proportion of true positives that the researcher was able to accurately anticipate. The fact that the hybrid model had the highest recall suggests that it correctly identified the vast majority of scenarios in which farming would be effective.

The number of questions that are considered to be correct and the number of correct responses is both factored into the F-score. If your F-score is high, it indicates that both your accuracy and your recall are up to par with what is expected of you. The hybrid model produced the best F-score, suggesting that a favourable ratio of precision to recall was accomplished. This was demonstrated by the fact that the ratio was reached.

The CNN+LSTM hybrid model emerges victorious over its competition in terms of accuracy in forecasting agricultural appropriateness for the dataset that was presented in agriculture. This model also prevails in terms of all other criteria. The findings of the research indicate that this particular model is the most successful.

6. Conclusion

The application of convolutional neural networks (CNN) and long short-term memory networks (LSTM) for the purpose of determining whether or not a given area is suitable for farming represents a significant step forward in the agricultural predictive modelling process. This method combines the benefits of CNNs and LSTMs, bringing together their respective strengths in the extraction of spatial properties and the recognition of temporal patterns. CNNs have a stronger ability to recognise spatial patterns in data, which can help images of crop health, soil conditions, and even satellite imaging. Combining this model with LSTMs, which are skilled in managing time-series data such as weather patterns and historical yields, can result in the creation of a powerful and all-encompassing instrument. This all-encompassing technique makes certain that the spatial intricacies of farming landscapes as well as the temporal fluctuations of data pertaining to agriculture are both taken into consideration. In particular, utilising this strategy guarantees that each of these factors will be taken into account. The accuracy and timeliness of the guidance provided to farmers has been significantly enhanced thanks to predictive models that make use of the benefits offered by convolutional neural networks (CNNs) and long short-term memory (LSTMs). This not only makes farm management more effective, but it also increases the chances of higher yields by making the most of the resources that are already available and reducing the likelihood of unfavourable results. With the application of CNN and LSTM in predictive modelling, the future of agriculture has the potential to be more intelligent, less harmful to the environment, and technologically advanced.

Author contributions

Trapti Mishra[1]: Conceptualization, Methodology, Software, Field study, Data curation, Writing-Original draft preparation, Software, Validation., Field study **Pramod S Nair[2]**: Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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