

1 ViST: A Ubiquitous Model with Multimodal Fusion for Crop Growth Prediction

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6 Crop growth prediction can help agricultural workers to make accurate and reasonable decisions on farming activities. Existing
7 crop growth prediction models focus on one crop and train a single model for each crop. In this paper, we will develop a ubiquitous
8 growth prediction model for multiple crops, aiming to train a single model for multiple crops. A ubiquitous vision and sensor
9 transformer(ViST) model for crop growth prediction with image and sensor data is developed to achieve the goals. In the proposed
10 model, a cross-attention mechanism is proposed to implement the fusion of multimodal feature maps to reduce the computational
11 cost and balance the interactive effects between features. For training the model, we combine the data from multiple crops to train a
12 single (ViST) model. A sensor network system is constructed for the data collection on the farm that plants rice, soybean, and maize.
13 Experiment results show that the proposed ViST model has an excellent ubiquitous ability for crop growth prediction with multiple
14 crops.

15 CCS Concepts: • Computing methodologies → Artificial intelligence.

16 Additional Key Words and Phrases: crop growth prediction, ubiquitous model, multimodal learning, transformer module, cross-attention
17 mechanism

18 **ACM Reference Format:**

19 Junsheng Li, Ling Wang, Jie Liu, and Jinshan Tang. 2018. ViST: A Ubiquitous Model with Multimodal Fusion for Crop Growth Prediction.
20 *J. ACM* 37, 4, Article 111 (August 2018), 23 pages. <https://doi.org/XXXXXX.XXXXXXX>

21 1 INTRODUCTION

22 With the development of new technologies such as the Internet of things, big data, and artificial intelligence (AI),
23 modern agriculture has been dramatically changed. One major task in modern agriculture is to predict crop growth.
24 Crop growth prediction is used as the weather vane for agricultural activities. Accurate short-range prediction of
25 crop growth can help farmers manage fertilization, irrigation, and pesticide spraying effectively. With the effective
26 management of these agricultural activities, human and material resources can be reduced as much as possible, and the
27 final yields and economic benefits can be significantly improved. It can also reduce the use of pesticides that pollute the
28 environment and thus protect the ecological environment.

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There are many existing crop models for crop growth and yield prediction [1–3]. However, these models are designed for a specific crop and specific region and condition, which are not ubiquitous models. These models cannot be adaptive to any specific crop in different regions. The parameters and driving variables of the models are derived from the situation of a particular location, which can be measured and available under ideal conditions. Due to the inherent soil heterogeneity and the influence of farming methods on soil properties, the measured parameters will also be different. Because the biological system is too complex and many processes involved have to be fully understood, a ubiquitous model based on biology is different to build. A data-driven model with Neural Network makes it possible to build a ubiquitous model. Under the deep learning model, any dynamic systems, including crop systems, can be approximated through network structure design [4, 5].

In the past, much research has focused on multi-scale crop images collected by UAV or satellite remote sensing for crop growth and yield prediction [6–8]. These image data reflect the phenotype characteristics of crops. The dynamic changes of crop phenotypes, such as the Leaf Area Index, predict crop growth for a large region. Some researchers combine crop spectral data and soil and meteorological data for crop growth prediction [9–13]. However, these data-driven methods still need to be ubiquitous. The results are strongly related to collecting high-precision crop parameters and input data of crop environment. The data collection processing is costly, hardly leading to the use for farm management. The leaf area index (LAI) is a comprehensive index related to individual and group characteristics of crop growth [14]. The leaf area index (LAI) is selected as an prediction index of crop growth. LAI cannot reflect all individual and group characteristics and must be supplemented by ground monitoring [15]. Since images and sensors can provide adequate information on crop growth, images and sensors can be used as supplements to ground monitoring.

To approximate the objective function, a model has to be built to apply to multimodal and multi-dimension data. Most existing multimodal mechanisms exist in automotive drive and medical fields [16, 17]. Our work is the first to fuse crop RGB image and sensor data for low-cost crop growth prediction on farms. The multimodal fusion process fuses information from two or more modalities to realize information complementation and broaden the coverage of information contained in the input data. Different from other fields, the estimation model for crop growth by multimodal fusion has more challenges in generalization as each crop has its character. To solve this problem, we propose the ViST (Vision and Sensor Transformer) model, which can realize efficient information fusion for accurate prediction of crop growth.

Besides the fusion of multiple data resources for crop growth, we also investigate the possibility of hybrid training, which aims at developing a single network to predict the crop growth of multiple crops. In the past, many models for crop growth prediction were developed. However, all of these models were trained using a single crop, which means each crop needs a single model. On a farm, there are generally many crops. Training is time-consuming and complex for farmers if each crop needs a trained model. Thus, this paper aims to develop a ubiquitous model that could be used for multiple crops. A sensor network system is constructed for the data collection on the farm that plants rice, soybean, and maize.

The main contributions of this paper are as follows:

- We proposed a ViST (Vision and Sensor Transformer) model for crop growth, which can efficiently utilize a multimodal data fusion mechanism.
- We also investigated the possibility of hybrid training, which aims at developing a single network to predict crop growth of multiple crops.
- The proposed model was compared with other existing models using data from farms we collected, and the proposed model can obtain better performance than other current models.

105 2 RELATED WORK

106 107 2.1 Single-modality approaches for crop growth prediction

108 Single-modality approaches for crop growth prediction include two types of methods: image-only and non-image
109 sensor-only strategies. Image-based remote sensing technology for crop growth prediction is one of the image-only
110 approaches. Image-based remote sensing technology has attracted attention as it can estimate crop growth effectively
111 due to its ability to provide timely, dynamic, and macro-scale observations [18]. With the development of machine
112 learning techniques, image-based remote sensing technology for crop growth has developed further. They are often
113 combined with machine learning techniques to estimate crop growth [19–21]. However, the quality of images acquired
114 through traditional remote sensing is often affected by weather and cloud changes and thus affects the prediction.
115 Besides, remote sensing technology generally has high maintenance and operation costs, affecting its vast uses. Recently,
116 convenient image-based techniques based on UAV drew the researchers' attention [22–26]. By mounting a camera to a
117 UAV, high spatial resolution images of crops can be acquired and thus can be used for crop growth estimation. These
118 techniques are beneficial for small farms.

119 Non-image sensor-only approaches are also popular for growth prediction. Because crop growth is affected by
120 climate/weather and soil conditions [27–29], thus meteorological and soil sensors have been widely used to predict
121 crop growth attributes. These non-image sensor-only approaches often use machine learning techniques. Dahikar et al.
122 [30] proposed a crop prediction method by sensing various soil parameters and parameters related to the atmosphere
123 and using ANN for crop yield prediction in rural areas. O'Neal et al. [31] designed a fully connected network to predict
124 maize yield using local crop stage weather data and yield data from 1901 to 1996. Morimoto et al. [32] used a deep
125 learning model to identify changes in citrus sugar and citric acid content based on rainfall and sunshine duration data.
126 Drummond et al. [33] applied feedforward neural networks to estimate nonlinear relationships between soil parameters
127 and crop yields. Kitchen et al. [34] found that neural networks could provide the most accurate empirical model of the
128 data and fit the yield data well to soil and terrain features.

129 130 131 132 133 134 135 2.2 Multimodal learning for crop growth prediction

136 Image-only and non-image sensor-only approaches have shown impressive results in predicting crop growth [35].
137 However, regarding the integrity of information expression, the model obtained by a single modality still has certain
138 defects for missing information. One solution is to integrate the representations of these two modalities to take advantage
139 of their complementary advantages in crop growth prediction.

140 Many deep learning-based approaches have been developed to handle multimodal data [36–38]. Multimodal machine
141 learning has led to a wide range of applications: from audiovisual speech recognition (AVSR)[39], multimedia content
142 indexing and retrieval [40], understanding human multimodal behavior, multimodal emotion recognition [41], image
143 and video captioning [42], VQA[43], multimedia retrieval [44], to health analytics [45], etc. Huang et al. [46] proved from
144 a theoretical point of view that multimodal learning could fuse the information of single modalities and complement
145 each other so that the final effect of the model is better than that of a single modality.

146 In agriculture, there is some research on multimodal learning. Dang et al. [47] used DNN with a multilayer feedforward
147 perceptron(MLP) model for crop yield prediction. Chu et al. [48] proposed an end-to-end prediction model for summer
148 and winter rice yield based on MLP deep learning fusion. Two simple MLPS were used to extract spatial and temporal
149 features, and then these two simple MLP models were combined to mine the relationship between features and rice
150 yield. The model maintained stable convergence after 100 iterations. Maimaitijiang et al. [49] tried to use multimodal
151

157 data fusion to complete tasks related to crop growth. The combined multimodal information, such as canopy spectral,
158 structural, thermal, and texture features, are extracted. Input-level and middle-level feature fusion by MLP are used to
159 predict crop grain yield.
160

161 However, the previous work uses MLP for data fusion in the NN models. The problem is that it is suitable for
162 small-scale learning. When the model scale is enlarged, it will suffer from serious overfitting. Due to extensive data in
163 images, it is difficult for MLP to extract features efficiently [50]. In addition, the learning efficiency of fully connected
164 architectures is very low, which has long been confirmed by machine learning experiments. Inefficiency means that
165 more training data are needed to reach a certain level of performance. Many application scenarios cannot provide
166 enough data support, so it is necessary to introduce assumptions to improve the utilization efficiency of limited data.
167 Therefore, the application scenarios of the fully connected architecture are limited, and there are also problems of poor
168 interpretability and robustness.
169

170 With the success of Transformers and self-supervised learning, there has been increasing research on cross-modal
171 learning, such as vision-language pre-trained models (VLP)[51], images and lidar fusion[52], Audio set, Epic-Kitchens,
172 and VGGSound classification [53]. The attention adaptively generated by Transformer has good adaptability. Attention
173 can filter out a small amount of important information from a large amount of data, focus on this vital information, and
174 ignore the most unimportant information. The information is critical, and more weight can be assigned. That is, the
175 weight represents the importance of the data [54].
176

177 The multimodal fusion process fuses information from two or more modalities to realize information complementation
178 and broaden the coverage of information contained in the input data. [37] However, it inevitably adds much redundant
179 information. Therefore, a more effective way of information fusion and expression is needed.
180

181 A multimodal learning method based on Transformer[54] is proposed to complete the task of crop growth prediction.
182 Compared with MLP [49], Transformer can extract features efficiently on tasks with a large amount of data, such
183 as images and sensors. As a result, unnecessary calculations are reduced, and the efficiency and robustness of the
184 prediction model are improved. The modular structure of the Transformer model allows for flexible processing of
185 different types of inputs. Different types of features can be inputted into different modules of the Transformer and
186 combined for further processing. This structure makes it easier to expand the model to accommodate different types of
187 data, facilitating the fusion of multimodal data.
188

189 A cross-attention mechanism is proposed for fusing agricultural sensor and image data with fewer redundancy
190 calculations. Besides, there are significant differences between the representations and feature spaces of images and
191 sensor data. By using cross-attention mechanisms, images and sensor data can be jointly encoded and effectively
192 complemented based on their common features. This enables the model to handle multimodal data better.
193

3 VISION-AND-SENSOR TRANSFORMER MODEL

201 The proposed ViST overall network structure is shown in Figure 1. The inputs are crop images and sensor data. In
202 the framework, the MLP module and Linear Projection Flattened Patches module(LPFP) extract features from sensor
203 and image data, respectively. LPFP was introduced by ViT[55]. The transformer encoder is designed for data fusion.
204 Pooler and Linear modules are intended to reduce the dimension of features. The specific details of each module in the
205 framework are described below.
206

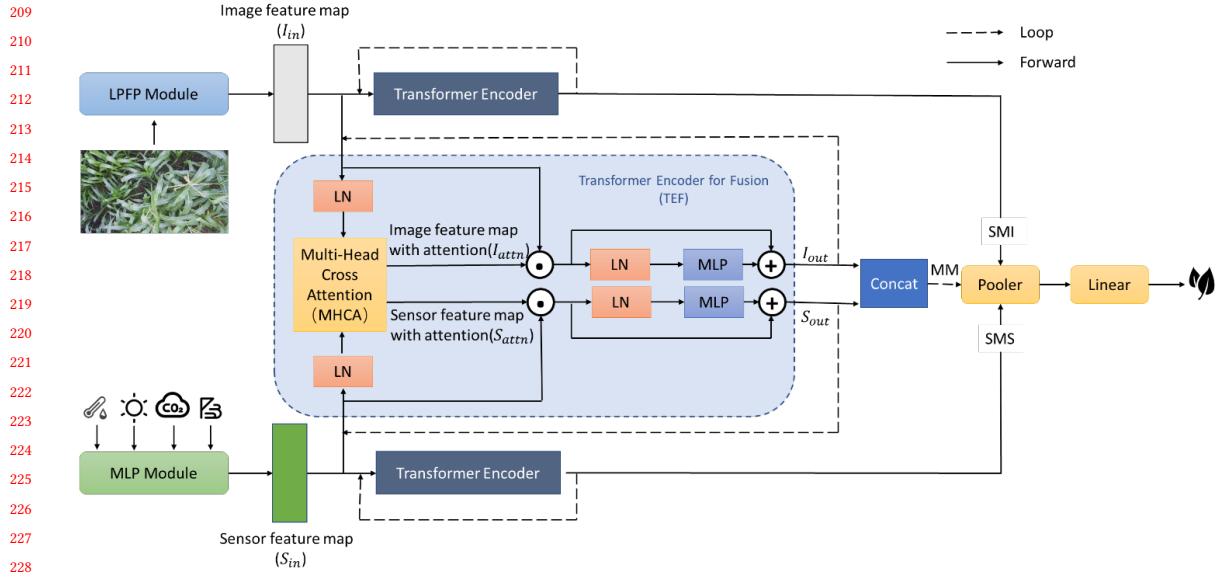


Fig. 1. The framework of ViST for growth prediction. Solid lines represent forward and dashed lines represent loop. The input of the ViST is sensor and image data. They are processed independently at MLP and LPFP modules, respectively. The features from the two modules are input to one Transformer Encoder for feature fusion. The encoder output is given to the Concat module with the output for Multiple Modalities (MM). At the same time, the features are sent separately to the other two Transformer encoders for self-attention mechanics. The outputs of these two transformer encoders are Single Modality with Image(SMI) and Single Modal with Sensor(SMS). The results of MM, SMI, and SMS are then input into the Pooler module to reduce the dimension of the features. Finally, the features are input to the linear layer module to output the leaf area index (LAI) value (in the range of [0,1]).

3.1 MLP Module

Generally speaking, image data has three channels for RGB, and each pixel has a value. But sensor data only has dozens of values. Therefore, the number of values for Sensor data is much less than those for image data. Image data will dominate if the two data types are directly integrated; Simultaneously, the sensor data will not be well expressed.

To solve this problem, sensor data was converted into feature maps. MLP module can amplify the characteristics of the sensor data. The sensor data are composed of weather data and soil data. The data are numerical and have 19 data items. After data preprocessing, the sensor data were arranged into one-dimensional vectors and input into the multilayer feedforward perceptron(MLP) module. The specific structure of the MLP module is shown in Figure 2.

Following the output of the MLP module, a one-dimensional vector containing 768 elements is generated, resulting in a vector size of 1×768 . This vector is then transformed into a 145×768 matrix using the following equation:

$$M_{out} = W_s \times M_{in} \quad (1)$$

where M_{in} refers to the 1×768 vector generated by the MLP module, which is then transformed into a 145×768 matrix, denoted as M_{out} . W_s is a 145×1 matrix whose elements are obtained through training the model.

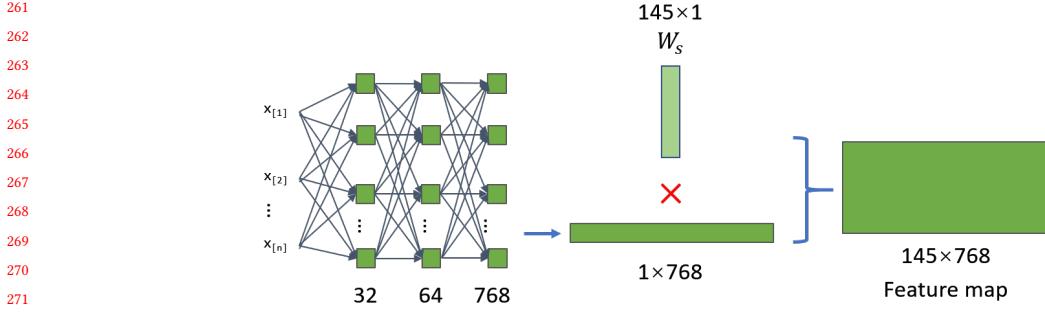


Fig. 2. Sensor input model structure. The MLP module is a multilayer perceptron. It has 19 neurons at the input layer and 768 neurons at the output layer. The two hidden layers contain 32 and 64 neurons, respectively. We found the performance using 2-layer MLP and 3-layer MLP doesn't have significant difference, thus we used the simpler 2-layer MLP.

3.2 Linear Projection Flattened Patches module

In this paper, the sensor data is mapped to the same dimension as the image features of the LPFP module to facilitate subsequent feature fusion operations. It is worth noting that the sensor features based on the MLP module do not require position information, and the input order of sensor data can be arbitrarily scrambled.

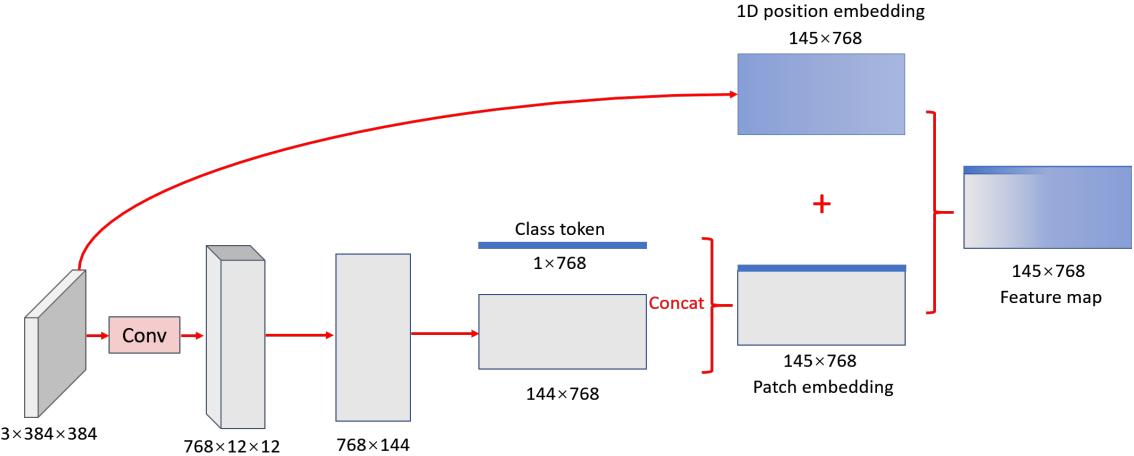


Fig. 3. Linear Projection Flattened Patches module. Linear Projection Flattened Patches divide the image into several equal small images and align the image feature map with the sensor features through matrix transformation.

The structure of the linear projection flattened patches module is shown in Figure 3. The input of the module is an image with a size of CHANNEL×HEIGHT×WIDTH ($C \times H \times W$). The 3D tensor corresponds to an RGB image. Before inputting the image, the image is adjusted to the size of $3 \times 384 \times 384$, as shown in the input in Figure 3. The image is divided into 768 blocks with the size of 12×12 by convolution operation. The convolution operation was performed using a kernel of size 32×32 . The stride of the convolution operation is 32. Each small image is flattened into 144 one-dimensional vectors, and 768 flattened one-dimensional vectors are successively connected into 768×144 vectors.

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313 The 768×144 vector is transposed to the 144×768 vectors to be fused with the feature vector from the sensor. Then, the
 314 144×768 feature vector is concatenated with the class token vector to generate patch embedding.
 315

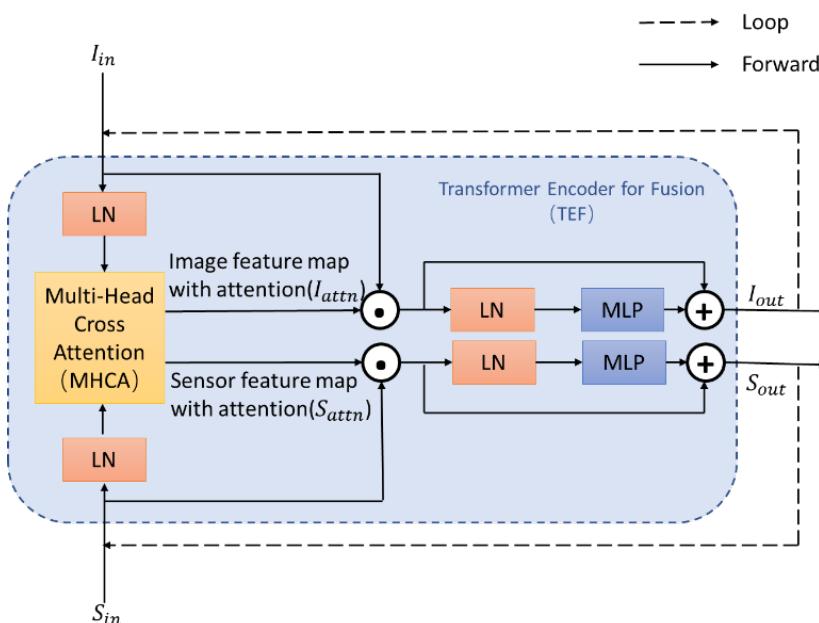
316 The Class Token is a specialized token that can represent the category information of an image. It is a vector that is
 317 typically added to the embedded representation of the image. The Class Token can provide additional information by
 318 encoding some global features that are shared by all images, which can help the model better understand the content of
 319 the images.
 320

321 The position information of 1D Position embedding is added to patch embedding to retain positional information.
 322 Both class token and 1D Position embedding refer to ViT [55]. The position information of each pixel in an image can
 323 be transformed into a high-dimensional vector, where each dimension of the vector represents the position of the pixel
 324 in a specific dimension of the image. This high-dimensional vector can be concatenated with the feature vector of
 325 each pixel (e.g., color information, texture information, etc.), resulting in a higher-dimensional feature vector. ViT has
 326 proved that the performance of 2D position embedding is not better than that of 1D position embedding, so 1D position
 327 embedding is chosen.
 328

329 Finally, the Patch embedding is added to the 1D position embedding to obtain the feature map of the image.
 330

331 The features of the image and the sensor are represented using vectors with the same dimensions. The vectors are
 332 ready to be input to the next transformer encoder for complete feature fusion.
 333

334 3.3 Transformer Encoder for fusion



360 Fig. 4. The structure of the Transformer Encoder for Fusion (TEF) model consists of alternating layers of Multi-Head Cross Attention
 361 (MHCA), multiple layer perceptron (MLP) and Layer Normalization (LN) modules. MHCA is the central module responsible for fusing
 362 the image and sensor features. The MLP is adopted from ViT, and the LN module is responsible for performing Layer Normalization
 363 operations.
 364

The Transformer Encoder for Fusion (TEF) model serves as the central model for multi-modal data fusion. The calculation process for TEF in Figure 4 is given as follows.

$$I_{attn}, S_{attn} = MHCA(I_{in}, S_{in}) \quad (2)$$

$$I_{out} = MLP(LN(I_{in} \cdot I_{attn})) + I_{in} \cdot I_{attn} \quad (3)$$

$$S_{out} = MLP(LN(S_{in} \cdot S_{attn})) + S_{in} \cdot S_{attn} \quad (4)$$

Here I_{attn} and S_{attn} are defined as the output of MHCA module, respectively. I_{attn}, S_{attn} are Image and Sensor Feature Map with attention, respectively. I_{in}, S_{in} are defined as the inputs of TEF, respectively. I_{out} and S_{out} are outputs of TEF, respectively. I_{in} and I_{out} are Image Feature Maps. S_{in} and S_{out} are Sensor Feature Maps. There are 12 loop computations for TEF. The output of TEF I_{out} and S_{out} are the input for TEF at next loop. After 12 loops is finished, I_{out} and S_{out} are given to next module.

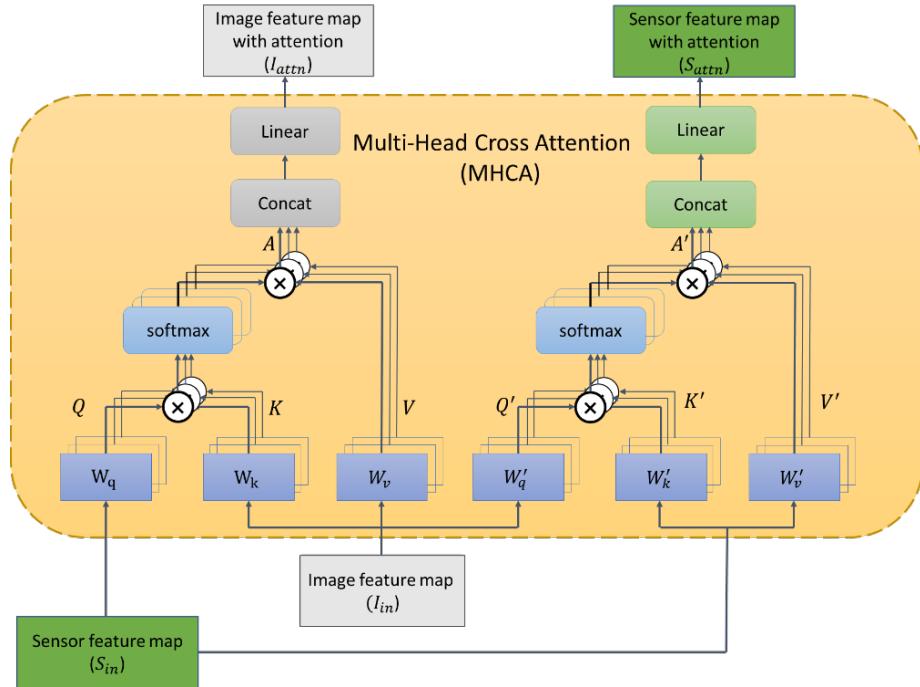


Fig. 5. The Multi-Head Cross Attention Module (MHCA) structure serves as a central component of the Transformer Encoder for Fusion. It operates by taking in both the image feature map (I_{in}) and the sensor feature map (S_{in}) as inputs. The module employs cross-attention mechanisms to investigate the interrelationships and associations among each feature map and between the two feature maps. Through this approach, the MHCA module achieves an improved ability to identify meaningful features from both modalities, generating an image feature map with attention (I_{attn}) and a sensor feature map with attention (S_{attn}) as outputs.

The Cross Attention module is proposed to model intra-modality relationships for image and sensor features. The structure of MHCA is shown in Figure 5. There are two branches to determine the parameters Query(Q, Q'), Key(K, K'), and Value (V, V'). One branch calculates Q, K, V for Image feature map with attention I_{attn} . The other calculates Q', K', V' for Sensor feature map with attention S_{attn} . The calculation process is given as followings:

$$Q = S_{in}W_q, K = I_{in}W_k, V = I_{in}W_v \quad (5)$$

$$A = softmax\left(\frac{QK^T}{\sqrt{C/h}}\right) V \quad (6)$$

$$Q' = I_{in}W'_q, K' = S_{in}W'_k, V' = S_{in}W'_v \quad (7)$$

$$A' = softmax\left(\frac{Q'K'^T}{\sqrt{C/h}}\right) V' \quad (8)$$

where $W_q, W_k, W_v, W'_q, W'_k, W'_v \in \mathbb{R}^{C \times (C/h)}$ are linear transformation matrix with learnable parameters. These multiple matrixes are computed by multi-head. C and h are the embedding dimension and number of heads, respectively. A and A' are results of equation 6 and equation 8, respectively. Multiple A and A' are concatenated, respectively. The sensor feature map S_{in} for one branch is used for query Q to compute K' and then update V' . The Image Feature Map I_{in} for another branch is used for query Q' to compute key K and value V . Therefore, these two branches exchange information between sensor and image features for semantic information sharing. The computation complexity of generating the attention map in cross-attention are linear rather than quadratic as in all-attention. The entire process for MHCA module is more efficient. And it can reduce the risk of overfitting.

3.4 Loss function

The leaf area index (LAI) data was manually collected from the farm and used as labels for the ViST model. Following data normalization, LAI values were scaled to a range of [0,1]. The loss function quantifies the discrepancy between the model's predicted value y' and the actual value y . This non-negative, real-valued function is typically expressed as $L(y, y')$ and serves as the foundation for the empirical risk function and the structural risk function.

In this paper, we approach crop growth prediction as a regression problem. A neural network with a single output node is typically used to solve regression problems, with the output value representing the predicted value. To evaluate the performance of our model, we use the mean square error loss function as the primary metric.

$$MSE(y, y') = \frac{\sum_{i=1}^n (y_i - y'_i)^2}{n} \quad (9)$$

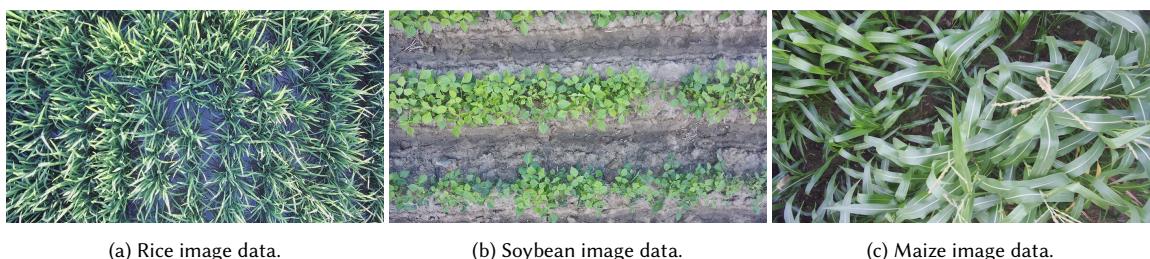
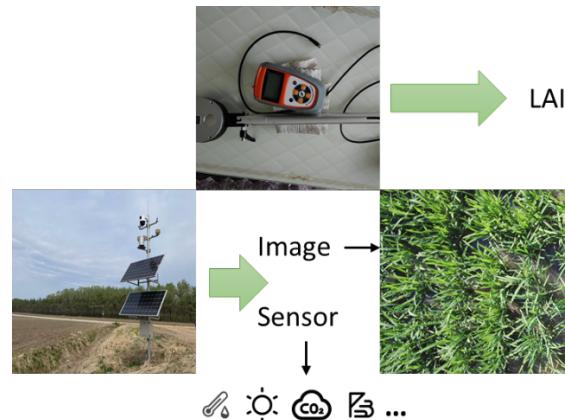
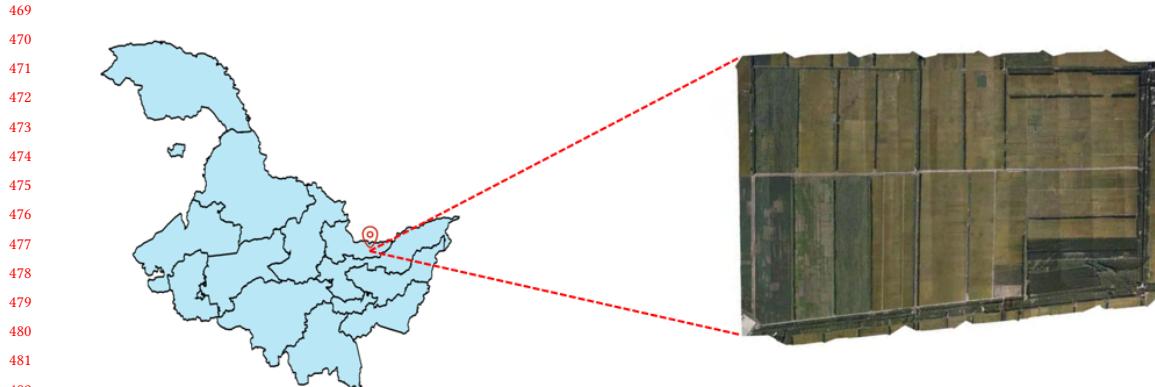
where n is the number of samples, y_i is the true value of the leaf area index for the i-th sample, and y'_i is the predicted value of the leaf area index for the i-th sample. The MSE serves as a measure of the accuracy of our model's output and is used to update the model parameters in subsequent iterations.

4 EXPERIMENTS AND RESULTS

In this section, we will present the methods used for data collection, describe the equipment and data format employed. Following data collection, both image and sensor data undergo preprocessing. The evaluation criteria for model performance and experimental details will also be outlined.

4.1 Data collection

The location for data acquisition is shown in Figure 6. The rice, maize, and soybean data were collected on farm. There are three sample points for each crop. There are totally 9 sample points on farm. The data acquisition device is shown



521 Table 1. Sensor data. The table lists the data items captured by the sensors and their corresponding units.

Data item	Unit
Carbon dioxide	PPM
Soil temperature	Celsius
Soil humidity	%
Air temperature	Celsius
Air humidity	%
Light intensity	Klux
Wind direction	degree
Wind speed	Meters per second
Air pressure	Hpa
PM10	PPM
PM2.5	PPM

536 in Figure 7. One device placed at each sample point on farm includes one camera and 11 number of sensors. LAI data
 537 were collected periodically using a hand-held device at each sample point for data alignment.

538 The crops are photographed from a top view. The images of rice, soybeans, and maize captured by the camera on
 539 the farm are shown in Figure 8(a)(b)(c), respectively. The height is set at 3 meters. The image format is RGB with a
 540 resolution of 3840×2160. The time interval between each image was two hours.

541 The collected items of sensors are shown in Table 1, including eleven sensor data types. The soil sensors are deployed
 542 in the ground at 10cm, 20cm, 30cm, 40cm, and 50cm depths, respectively. Air, light, and Wind sensors are deployed on
 543 the top of the IoT Device. The time interval of data collection for each sensor is half an hour. The image and sensor data
 544 were collected and uploaded to the cloud server periodically for storage and data analysis.

545 4.2 Data preprocessing

546 **Preprocessing of image data:** To ensure better convergence in backpropagation, the image data was normalized to a
 547 specific range using the Z-score method on each image's data.

$$548 \quad z = \frac{x - \mu}{\sigma} \quad (10)$$

549 In this study, where μ denotes the mean value, σ represents the standard deviation, x denotes the input data, and z
 550 denotes the output data. The mean and standard deviation of the three channels of the image were recorded, respectively.
 551 Specifically, the mean value of the normalized image was set to 0 on each channel, and the variance was set to 1.
 552 However, it should be noted that this normalization method may not be applicable to cases with small sample sizes, and
 553 is generally recommended to be used only when the sample size exceeds 30. Table 2 presents the normalized results of
 554 image calculation for rice, soybean, and maize.

555 **Preprocessing of sensor data:** To eliminate the influence of dimensions, we normalized each size using the following
 556 equation, as the numerical differences between dimensions in the sensor data were relatively large.

$$557 \quad x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (11)$$

558 where x_{min} is the minimum value, and x_{max} is the maximum value. $x_{normalized}$ is the normalized value.

559 The maximum and minimum values for each metric were saved in a separate file for data preprocessing when they
 560 were used for processing actual data. The processed data are shown in Table 3.

573
574
575 Table 2. Image standardized data. The table presents the mean and standard deviation values for the RGB channels of the images of
three crops, namely rice, soybean, and corn. These values were obtained through the normalization process described in the previous
section.

crop	channel	mean	standard deviation
rice	Channel 1	0.4452	0.1973
	Channel 2	0.5014	0.2035
	Channel 3	0.4292	0.183
soybean	Channel 1	0.5	0.1517
	Channel 2	0.5355	0.1641
	Channel 3	0.487	0.1497
corn	Channel 1	0.4452	0.1973
	Channel 2	0.5014	0.2035
	Channel 3	0.4292	0.183

589
590 Table 3. Sensor input metrics preprocessing. The table includes the indicators for sensor data processing, as well as their maximum
591 and minimum values.

Indicators	Minimum	Maximum
Carbon dioxide	364	636
Soil temperature for 10 centimeters depth	18.1	25.1
Soil temperature for 20 centimeters depth	18.3	23
Soil temperature for 30 centimeters depth	18.3	22.1
Soil temperature for 40 centimeters depth	-30	-30
Soil temperature for 50 centimeters depth	17.1	21.2
Soil humidity for 10 centimeters depth	46.8	80.6
Soil humidity for 20 centimeters depth	53	75.6
Soil humidity for 30 centimeters depth	55.2	79.5
Soil humidity for 40 centimeters depth	0	80.6
Soil humidity for 50 centimeters depth	67.3	81.5
Air humidity	31	98.53
PM10	0	128
PM2.5	0	55
Air pressure	981.1	1005.1
Light intensity	0	200
Air temperature	16.37	30.99
Wind direction	0	359.8
Wind speed	0	6.68
LAI	1.3075	1.91

616
617 **Processing of LAI data:** In order to ensure better convergence in backpropagation, the image data were normalized
618 to a specific range using the Z-score method. For each crop, three sets of image and sensor devices were placed at the
619 same position as the camera when measuring the LAI. During the collection of LAI data, hand-held devices capture a
620 part of areas covered by the camera device. LAI data were collected every 5 days. In order to obtain more data, the
621 piecewise cubic Hermite interpolation polynomial (PCHIP) method was used, as described by Fritsch and Carlson [56].
622 LAI data were available for each day and were interpolated for three sample points of rice, soybean, and maize as
623
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625 shown in Figure 9(a),(b),(c), respectively. The left side of the figure shows the original data and the right side shows the
 626 interpolated data. The interpolated data appear smoother, as can be seen from the curves.
 627

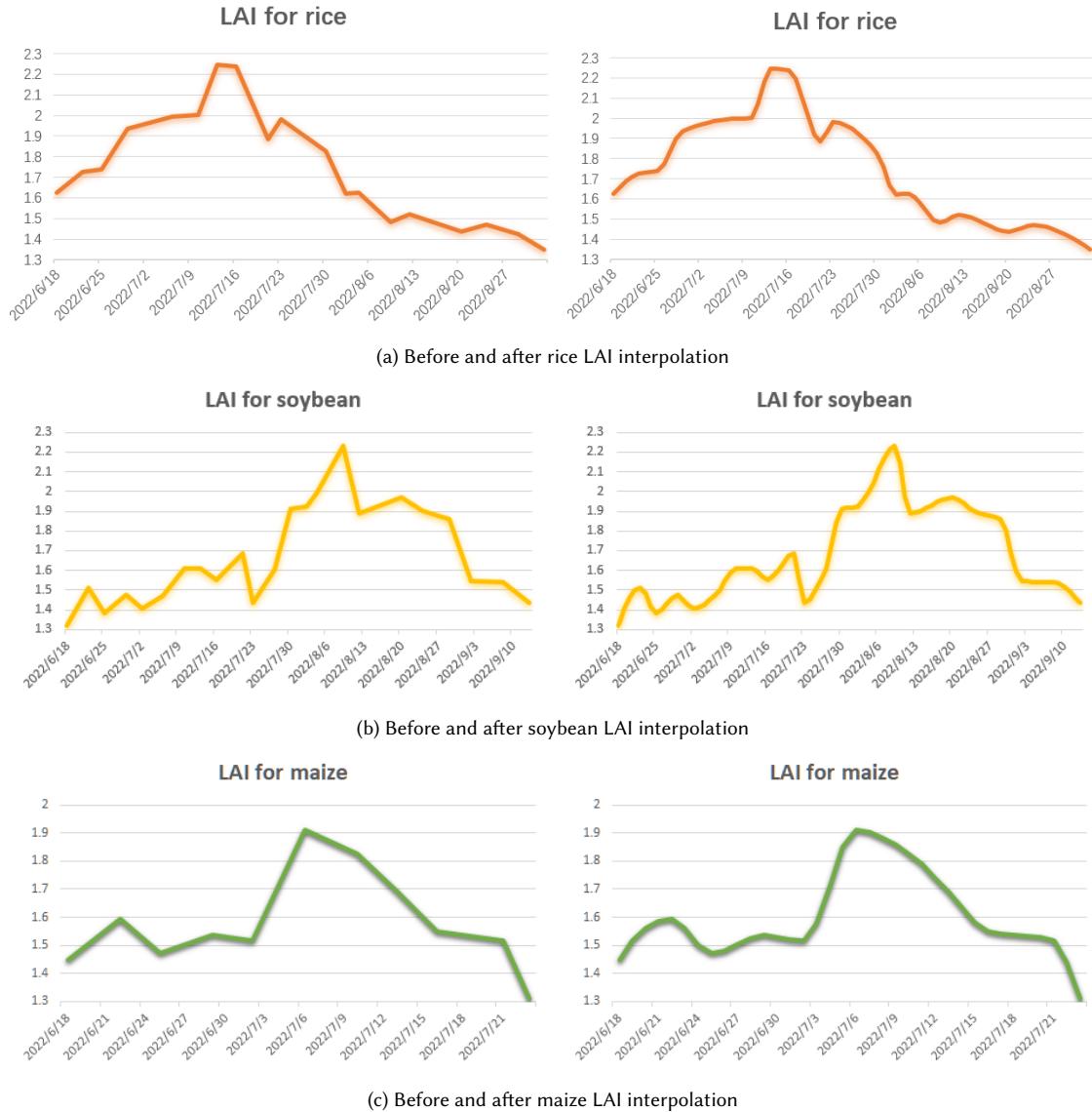


Fig. 9. LAI data preprocessing. The figure shows the leaf area index data before and after interpolation. The horizontal axis represents time, and the vertical axis represents the leaf area index.

Data alignment: One sample includes image data, sensor data, and a label – LAI data. The image data, sensor data, and LAI data were aligned based on their respective sampling location and time. Each image was captured at a two-hour interval, while the sensors’ sampling frequency was every half hour. The time alignment between the data sets was

677 established on a half-hour basis. Due to the smaller quantity of image data relative to the sensor data, four samples
 678 collected over a two-hour period corresponded to a single image. Notably, there is only one LAI data point per day; this
 679 means that forty-eight samples share the same LAI label.
 680

681 **Training and test sets:** For each crop, three sample points were selected, yielding a total of nine observation points
 682 on the farm. Two of the sample points were utilized for model training, while the remaining sample point was used for
 683 model testing. Cross-validation was carried out across different sample points for each crop to prevent the problem of
 684 using the same sample data for both training and testing, which could result in a smaller difference in the data gradient.
 685

686 The amount of data utilized in the experiment is illustrated in Fig. 4, with "days" denoting the duration of data
 687 collection. "Train sample" and "Test sample" refer to the number of data instances employed for training and testing,
 688 respectively.
 689

690
 691 Table 4. The quantity of experimental data.
 692

Crop	Days	Train sample	Test sample
Rice	83	7968	3984
Soybean	87	8352	4176
Maize	83	7968	3984

699 4.3 Evaluation Metrics 700

701 Mean square error (MSE), mean Absolute error (MAE), Mean Absolute Percentage Error(MAPE) and Symmetric Mean
 702 Absolute Percentage Error(SMAPE) are used to predict the performance of various models. MSE is the same as the loss
 703 function. MAE is the sum of the absolute differences between the target and prediction values.
 704

$$705 \quad 706 \quad 707 MAE = \frac{\sum_i^n |y_i - y'_i|}{n} \quad (12)$$

708 where y'_i is the evaluated value of the model, y_i is the real value, and n is the total number of samples.
 709

710 The Mean Square Error (MSE) is the mean of the squared differences between the model's evaluated value, and the
 711 actual sample value y . The formula is as follows:
 712

$$713 \quad 714 MSE = \frac{\sum_{i=1}^n (y'_i - y_i)^2}{n} \quad (13)$$

715 where y_i and y'_i , i are the true value and the corresponding evaluated value for the first sample, and n is the number
 716 of samples.
 717

718 MAPE is a commonly used performance metric in estimation. It measures the accuracy of a estimation by calculating
 719 the absolute percentage difference between the estimation value y'_i the actual value y_i , and then take the average of all
 720 the absolute percentage differences. The formula for calculating MAPE is as follows:
 721

$$722 \quad 723 MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{y'_i - y_i}{y_i} \right| \quad (14)$$

724 where n is the number of samples, y_i is the actual value, and y'_i is the estimate value.
 725

726 SMAPE is a widely used metric for evaluating the accuracy of forecasting models. It is a symmetric error that
 727 calculates the average percentage difference between the actual and evaluated values . Unlike other error measures,
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729 SMAPE takes into account the magnitude of the actual values, making it a more reliable metric for comparing the
 730 accuracy of different forecasting models. The formula for calculating SMAPE is as follows:
 731

$$732 \quad 733 \quad 734 \quad SMAPE = \frac{100\%}{n} \sum_{i=1}^n \frac{|y'_i - y_i|}{(|y'_i| + |y_i|)/2} \quad (15)$$

735 where n , y_i and y'_i are same as the symbols in MAPE formula. SMAPE ranges from 0% to 200%, with lower values
 736 indicating better accuracy.
 737

738 4.4 Experiments and results

740 In this section, we present the extensive experiments conducted to demonstrate the effectiveness of our proposed
 741 ViST over existing methods. Our model was compared with the state-of-the-art models, such as Rice-Fusion [57], Rice-
 742 Transformer [58], CNN-Transformer [59], DNNF1, and DNNF2 [49]. While both DNNF1 and DNNF2 are multimodal
 743 models developed for soybean yield prediction, Rice-Fusion and Rice-Transformer employ multimodal approaches to
 744 diagnose rice diseases. The CNN-Transformer model was proposed to classify crops based on multitemporal data. In
 745 terms of comparison, the input and output to these models were kept the same as for our ViST model. Finally, the
 746 output of all models was evaluated based on the LAI value representing the crop growth status.
 747

748 ViST was subjected to ablation studies with regards to its input modes, including image-only data, sensor-only data,
 749 and multimodality data. The performance of each model was evaluated using a range of metrics, including MAE, MSE,
 750 MAPE, and SMAPE which are presented in Equations 12, 13, 14, and 15, respectively.
 751

752 The preprocessed data were utilized to train each model using the primary hyperparameters of ViST, which are
 753 outlined in Table 5. An Adam optimizer was employed, with a weight decay of 0.0001, and all models were trained on
 754 a GeForce RTX 3090 GPU. To dynamically adjust the learning rate, the cosine annealing strategy was implemented.
 755 The maximum number of iterations was determined based on the sample size and epoch, resulting in a monotonically
 756 decreasing learning rate with increasing epochs during the training process. The ViST model's primary hyperparameters
 757 can also be found in Table 5. Random normal distribution was used to initialize the parameters of each model. For the
 758 ablation experiment, the MM, SMI, and SMS were used as inputs for the model.
 759

760 Table 5. Main hyperparameters of the model.
 761

764 Parameter	765 Parameter size
766 hidden size	768 768
767 head num	12
768 layer num	12
769 MLP ratio	4
770 drop rate	0.1
771 sensor num	19
772 epoch	50
773 batch size	32
774 weight decay	0.0001
775 learning rate	0.0001

776 4.4.1 Experiments and results for a single crop. In this section, we evaluated the performance of our model on three crops
 777 - rice, soybean, and maize. Firstly, we compared the model's performance using single modality data and multimodality
 778

781 data, as discussed in Section A. Secondly, we compared the performance of our ViST model with that of other models,
 782 as outlined in Section B.
 783

784 **A.Performance Comparison of ViST model with single modality data and multimodality data**

785 The ViST model was trained for each crop with three different data input modes: image data, sensor data, both of
 786 image and sensor data. Thus, three trained models were obtained for each crop.
 787

788 Table 6. ViST model test results for different input modes.
 789

Crop	Input mode	MSE	MAE	MAPE	SMAPE
rice	Sensor	0.00227	0.03469	0.14928	13.1395
	Image	0.00548	0.0527	0.27484	20.19456
	Multimodality	0.00244	0.01344	0.05614	5.26049
soybean	Sensor	0.03201	0.12261	0.67907	34.33472
	Image	0.00536	0.04973	0.31889	15.41658
	Multimodality	0.00007	0.00351	0.02644	2.06496
maize	Sensor	0.00183	0.03185	0.14455	12.50781
	Image	0.00409	0.04577	0.19804	13.61606
	Multimodality	0.00003	0.00304	0.01768	1.53183

803 After the trained models were obtained, we used the data from the test dataset to test the models. The performance
 804 of the ViST model for test dataset is shown in table 6.
 805

806 It is shown that the multimodality mode has achieved the lowest value of the prediction indicators among three modes
 807 for three crops. As four indicators have shown the same trend on the experiment results, MAE is used to analyze the
 808 performance of the ViST model. In the rice experiment, the value of MAE decreases by, 61.25%, 74.49% compared to that
 809 of the sensor and image mode, respectively. In the soybean experiment, the value of MAE decreases by 97.13%, 92.94%,
 810 compared to that of the sensor and image mode, respectively. In the maize experiment, the value of MAE decreases
 811 by 90.45%, 93.35%, compared to that of the sensor and image mode, respectively. Therefore, it can be concluded that
 812 combining image and sensor data significantly improves the performance for ViST model. And both sensor and image
 813 data have almost equal contribution for model training.
 814

815 For rice, sensors are more effective than images because there is little difference in rice images during growth and
 816 leaf features are not prominent. For soybeans, images are more effective than sensors because the image features change
 817 significantly during growth. There is little difference between image and sensor data for corn, and both are effective in
 818 reflecting crop growth because error rates for various evaluation indices are relatively small.
 819

820 Using image analysis, crop surface texture features, such as color, texture, and shape, can be analyzed to infer the
 821 healthy status of the crop, including whether it is growing well and whether it is affected by pests and diseases. Sensor
 822 data can capture changes in environmental factors, such as temperature, humidity, light, and soil, to assess their impact
 823 on crop growth. For example, excessive drought or excessive moisture can have a negative effect on crop growth.
 824 By comprehensively analyzing these two aspects of information, crop growth can be more accurately evaluated, and
 825 appropriate agricultural management measures can be adjusted accordingly.
 826

827 In the experiments on rice, soybeans, and corn, the multi-modality results were better than the single-modality results.
 828 Multi-modal data can supplement the information that is lacking in single-modality data, completing the information gap.
 829 For example, images only reflect surface information of the crop, while sensors only reflect environmental information. If
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only single modality data is used, many important pieces of information will be ignored. By integrating multiple types of information, different types of information can complement each other, improving the accuracy and comprehensiveness of data analysis.

The fusion of image and sensor multi-modal data can complete noise suppression. Noise on the data is common, especially in sensor data processing. However, multi-modal data can reduce noise on the data by fusing the data, which is more robust than single modality data analysis.

Single-modality data is more susceptible to interference than multi-modality data, which is more robust. Sensor data is often affected by various external environmental factors (such as rain, dust, and occlusion), which can affect data accuracy. Conversely, image data is less affected by external factors. Therefore, in multi-modality data analysis, the combination of image data significantly improves data accuracy and robustness.

Thus, the complementary nature, noise suppression, and robustness of multi-modal data analysis can more comprehensively understand things' essence and more accurately describe the actual situation.

B.Comparison with other models

In this Section, we compared the proposed ViST model with other models: DNNF1, DNNF2, CNN-Transformer, Rice-Fusion, Rice-Transformer . All three models were trained on rice, soybean, and maize data, respectively.

Table 7. The comparative experimental test results of rice.

Model	MSE	MAE	MAPE	SMAPE
CNN-Transformer	0.00024	0.01368	0.04287	4.3371
DNNF1	0.00177	0.01775	0.08548	7.21533
DNNF2	0.00333	0.02816	0.11206	10.303
Rice-Fusion	0.00024	0.01065	0.04215	3.95636
Rice-Transformer	0.00244	0.01344	0.05614	5.26049
ViST	0.00023	0.00923	0.03263	3.15724

Table 7 shows the experimental results of various models when applied to the rice dataset. The ViST model showed the best performance on all prediction metrics, implying its excellent performance in estimating rice growth. In the average, ViST lowered MSE by 55.80%, MAE by 38.48%, MAPE by 44.21%, and SMAPE by 42.59%. Compared to the other models, the ViST model shows better performance in accuracy and stability, especially when compared to DNNF1 and DNNF2. For instance, compared to DNNF1, ViST lowered MSE by 87.01%, MAE by 48.00%, MAPE by 61.83%, and SMAPE by 56.24%. It is also shown that ViST has almost same value on MSE with CNN-Transformer and Rice-Fusion model.

Table 8. The comparative experimental test results of soybean.

Model	MSE	MAE	MAPE	SMAPE
CNN-Transformer	0.00013	0.00749	0.0705	3.43951
DNNF1	0.00016	0.00958	0.05863	4.10262
DNNF2	0.00091	0.01597	0.08465	6.45109
Rice-Fusion	0.00018	0.00656	0.0969	3.74191
Rice-Transformer	0.00014	0.00478	0.08859	3.17471
ViST	0.00007	0.00351	0.02644	2.06496

Similarly to Table 7, Table 8 presents the experimental results of ViST and other comparative models. The experiments in Table 8 use soybean data as the dataset. By considering the improvement ratios relative to the other models, it is evident that ViST achieves significant enhancements across all four metrics, with the most notable improvements visible on the MAE and MAPE metrics. Regarding the MSE metric, ViST achieves reductions of 56.25%, 92.31%, 61.11%, and 50.00% compared to DNNF1, DNNF2, Rice-Fusion, and Rice-Transformer, respectively. Furthermore, ViST decreases the error by 46.15% relative to CNN-Transformer.

Table 9. The comparative experimental test results of maize.

Model	MSE	MAE	MAPE	SMAPE
CNN-Transformer	0.00013	0.00805	0.03245	4.27382
DNNF1	0.00026	0.00926	0.05208	4.83925
DNNF2	0.00009	0.00775	0.02958	3.10525
Rice-Fusion	0.00007	0.00609	0.01712	1.71803
Rice-Transformer	0.00012	0.00672	0.02436	2.39245
ViST	0.00003	0.00304	0.01768	1.53183

Table 9 shows the experimental results of various models when applied to the maize dataset. The Rice-Fusion model exhibits good performance across four performance metrics, though slightly worse than ViST in terms of MAPE and SMAPE. Despite this, it still outperforms other models. The CNN-Transformer model demonstrates intermediate performance across the four metrics, slightly outperforming the DNNF1 and DNNF2 models with only small variations. It is apparent that the ViST model exhibits a reduction in error percentages greater than 50% for both MAE and MSE metrics. This suggests that the ViST model is able to more accurately predict experimental data and is more stable and reliable in comparison to other models.

The result for three crops compared with other models indicates that the visual and spatiotemporal information captured by ViST is critical in estimating rice growth accurately. Cross attention mechanics can effectively extract texture from leaf image and fusion sensor data with image feature. This suggests that the ViST model is able to more accurately evaluate experimental data and is more stable and reliable in comparison to other models.

Table 10. The comparative experimental test results for hybrid.

Model	MSE	MAE	MAPE	SMAPE
CNN-Transformer	0.00019	0.00822	0.03928	2.994976
DNNF1	0.00141	0.01928	0.09484	7.311991
DNNF2	0.00083	0.01388	0.04452	4.104376
Rice-Fusion	0.00024	0.00857	0.04541	3.579631
Rice-Transformer	0.00038	0.00614	0.03564	2.467895
ViST	0.00014	0.00591	0.02775	2.408083

4.4.2 Experiments and results for combined data training. The data from three crops were combined and used to train the model to test the model's generalization ability for the growth prediction of multiple crops. If only a single crop dataset is used to train the model, the model will focus too much on the characteristics of that crop, increasing the risk of overfitting. However, training the model with multiple crop datasets can reduce the risk of overfitting and improve

the model's stability. With the application of many artificial intelligence technologies, data in the field of agriculture has become very rich. However, the amount of data for each crop itself is not large. Therefore, training the model with multiple agricultural datasets can better utilize limited data resources and improve the model's applicability. Table 10 shows the results of ViST, DNNF1, DNNF2, CNN-Transformer, Rice-Fusion, Rice-Transformer models with the hybrid data set. The ViST model outperforms other models, particularly in terms of MAPE and SMAPE with higher accuracy. ViST's MAE performance is superior to other models, showing a 28.10%, 3.75%, and 31.04% reduction compared to the CNN-Transformer, Rice-Transformer, and Rice-Fusion models, respectively. Furthermore, ViST's outstanding performance in MSE indicates its ability to capture data features effectively, with reductions of 26.32%, 63.16%, and 41.47% compared to the CNN-Transformer, Rice-Transformer, and Rice-Fusion models, respectively.

The cross-attention mechanism adopted in ViST can fuse information from input data better, thus improving model performance and generalization capability. The performance of DNNF1 and DNNF2 based on multi-layer perceptron is worst due to their lack of complexity and flexibility in model structure, resulting in ineffective handling of various crop growth estimation tasks compared to ViST.

Table 11. Comparison Results of ViST model with different crops as input.

Train data	Test data	MSE	MAE	MAPE	SMAPE
Rice	Rice	0.00244	0.01344	0.05614	5.26049
Soybean	Soybean	0.00007	0.00351	0.02644	2.06496
Maize	Maize	0.00003	0.00304	0.01768	1.53183
Three crops	Three crops	0.00014	0.00591	0.02775	2.40808

The table presents the results of ViST for four sets of experiments involving rice, soybean, corn, and a mixture of the three crops data. The results on the ubiquitous ability of ViST are shown in Table 11. The model for Maize data exhibits relatively lower prediction errors compared to other crop data. For example, in terms of the SMAPE metric, the error value of maize is 1.53%, while the error values of rice, soybean, and a mixture of three crops are 5.26%, 2.06%, and 2.41%, respectively. It can be seen that maize shows better performance. The reason is that Maize has the most feature.

In the mixed experiment of the three crops, the error values of all prediction indicators are slightly increased relative to the single crop experiment, but the magnitude of the increase is small. This indicates that ViST exhibits a high level of prediction accuracy and robustness in handling multi-crop information, and therefore has high practical value for agricultural production applications. As training data is derived from various crops, inter-crop differences may exist and may affect the accuracy and stability of the model. The efficacy of combined training, with the exception of training with rice data, is comparatively suboptimal in contrast to that of other training with soybean and maize data.

4.4.3 Experiments and results for speed test. From experimental results in Figure 10, it is shown that the inference speed of ViST is much close to that of Rice-Fusion and Rice-Transformer. Compared to CNN-Transformer, DNNF1, and DNNF2, ViST's inference time is approximately 50% of theirs. The CNN model requires more convolution operations, resulting in a relatively greater computational load and slower inference speeds. The multilayer perceptron model entails a larger number of parameters and computational load, leading to slower inference speeds. The performance of DNNF1 and DNNF2 based on multi-layer perceptron is worst due to their lack of complexity and flexibility in model structure, resulting in ineffective handling of various crop growth estimation tasks compared to ViST. Although DNNF1 and DNNF2 are simple, the fusion of images and sensors results in unsatisfactory performance.

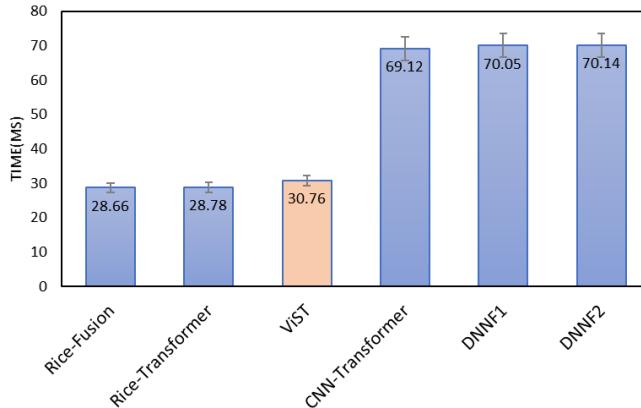


Fig. 10. Speed test results of the models. To compare the inference speed of models, each model performed 1000 inference runs, and the average result was taken as the final outcome. The horizontal axis represents the model name, and the vertical axis represents the average time for each inference run, in milliseconds. Each experimental result has an error rate of $\pm 5\%$.

5 CONCLUSION AND FUTURE DIRECTIONS

This paper has proposed a Transformer-based ViST model for crop growth prediction by image and sensor data on a farm. The cross-attention mechanism in the model was used to improve the effect of model data fusion. The data of the three crops were trained together as input to the model. The model not only achieves high accuracy but also maintains a relatively fast speed. Experiment results show that the model with multimodality data can improve crop growth predication. Although the ViST model has achieved good results, there are still a number of limitations. As the model requires cross-modal feature fusion, this may increase the computational cost and training time of the model. And the ubiquitous of the model needs to be further validated in different crops to determine its applicability and generalizability. In the future, more crop growth data will be collected for model optimization. Furthermore, investigating the model's use in practical agricultural production can assist farmers in better decision-making and production management.

ACKNOWLEDGMENTS

This research is supported by New generation artificial intelligent program, No.21ZD0110900 in CHINA, Heilongjiang NSF funding, No. LH202F022.

REFERENCES

- [1] Donald Gaydon and Christian Roth. 2014. *SAC Monograph: The SAARC-Australia Project-Developing Capacity in Cropping Systems Modelling for South Asia*.
- [2] N Brisson, C Gary, E Justes, R Roche, B Mary, D Riponche, D Zimmer, J Sierra, P Bertuzzi, P Burger, F Bussière, Y.M Cabidoche, P Cellier, P Debaeke, J.P Gaudillière, C Hénault, F Maraux, B Seguin, and H Sinoquet. 2003. An Overview of the Crop Model Stics. *European Journal of Agronomy* 18, 3 (2003), 309–332. [https://doi.org/10.1016/S1161-0301\(02\)00110-7](https://doi.org/10.1016/S1161-0301(02)00110-7)
- [3] HL Boogaard, CA Van Diepen, RP Rotter, JMCA Cabrera, and HH Van Laar. 1998. WOFOST 7.1; user's guide for the WOFOST 7.1 crop growth simulation model and WOFOST Control Center 1.5. (1998).
- [4] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. 2015. Deep Learning. *nature* 521, 7553 (2015), 436–444.
- [5] Zilong Hu, Jinshan Tang, Ping Zhang, and Jingfeng Jiang. 2020. Deep learning for the identification of bruised apples by fusing 3D deep features for apple grading systems. *Mechanical Systems and Signal Processing* 145 (2020), 106922–.
- [6] Kaili Wang, Keyu Chen, Huiyu Du, Shuang Liu, Jingwen Xu, Junfang Zhao, Houlin Chen, Yujun Liu, and Yang Liu. 2022. New Image Dataset and New Negative Sample Judgment Method for Crop Pest Recognition Based on Deep Learning Models. *Ecological Informatics* 69 (2022), 101620.

- 1041 <https://doi.org/10.1016/j.ecoinf.2022.101620>
- 1042 [7] Jibo Yue, Guijun Yang, Qingju Tian, Haikuan Feng, Kaijian Xu, and Chengquan Zhou. 2019. Estimate of Winter-Wheat above-Ground Biomass
1043 Based on UAV Ultrahigh-Ground-Resolution Image Textures and Vegetation Indices. *ISPRS Journal of Photogrammetry and Remote Sensing* 150
1044 (2019), 226–244. <https://doi.org/10.1016/j.isprsjprs.2019.02.022>
- 1045 [8] Mehmet Ozgur Turkoglu, Stefano D'Aronco, Gregor Perich, Frank Liebisch, Constantin Streit, Konrad Schindler, and Jan Dirk Wegner. 2021.
1046 Crop Mapping from Image Time Series: Deep Learning with Multi-Scale Label Hierarchies. *Remote Sensing of Environment* 264 (2021), 112603.
1047 <https://doi.org/10.1016/j.rse.2021.112603>
- 1048 [9] Miroslav Trnka, Josef Eitzinger, Pavel Kapler, Martin Dubrovský, Daniela Semerádová, Zdeněk Žalud, and Herbert Formayer. 2007. Effect of Estimated
1049 Daily Global Solar Radiation Data on the Results of Crop Growth Models. *Sensors* 7, 10 (Oct. 2007), 2330–2362. <https://doi.org/10.3390/s7102330>
- 1050 [10] Tanhim Islam, Tanjir Alam Chisty, and Amitabha Chakrabarty. 2018. A Deep Neural Network Approach for Crop Selection and Yield Prediction in
1051 Bangladesh. In *2018 IEEE Region 10 Humanitarian Technology Conference (R10-HTC)*. 1–6. <https://doi.org/10.1109/R10-HTC.2018.8629828>
- 1052 [11] Omololu M Adisa, Joel O Botai, Abiodun M Adeola, Abubeker Hassen, Christina M Botai, Daniel Darkey, and Eyob Tesfamariam. 2019. Application
1053 of Artificial Neural Network for Predicting Maize Production in South Africa. *Sustainability* 11, 4 (2019), 1145.
- 1054 [12] Jing Liu, CE Goering, and Lei Tian. 2001. A Neural Network for Setting Target Corn Yields. *Transactions of the ASAE* 44, 3 (2001), 705.
- 1055 [13] Kanichiro Matsumura, Carlos F Gaitan, Kenji Sugimoto, Alex J Cannon, and William W Hsieh. 2015. Maize Yield Forecasting by Linear Regression
1056 and Artificial Neural Networks in Jilin, China. *The Journal of Agricultural Science* 153, 3 (2015), 399–410.
- 1057 [14] Zhiyuan Pei Bangjie Yang. 1999. The definition of crop growth and remote sensing monitoring. *Transactions of the CSAE* 03 (1999), 214–218.
- 1058 [15] Toby N Carlson and David A Ripley. 1997. On the Relation between NDVI, Fractional Vegetation Cover, and Leaf Area Index. *Remote sensing of
1059 Environment* 62, 3 (1997), 241–252.
- 1060 [16] Zhe Guo, Xiang Li, Heng Huang, Ning Guo, and Quanzheng Li. 2019. Deep learning-based image segmentation on multimodal medical imaging.
1061 *IEEE Transactions on Radiation and Plasma Medical Sciences* 3, 2 (2019), 162–169.
- 1062 [17] Yi Xiao, Felipe Codevilla, Akhil Gurram, Onay Urfalioglu, and Antonio M. López. 2022. Multimodal End-to-End Autonomous Driving. *IEEE
1063 Transactions on Intelligent Transportation Systems* 23, 1 (2022), 537–547. <https://doi.org/10.1109/TITS.2020.3013234>
- 1064 [18] Zhongxin Chen, Huajun Tang, Jianqiang Ren, Pei Leng, Yun Shi, Limin Wang, Jia Liu, Yanmin Yao, Wenbin Wu, and Hasituya. 2016. Progress and
1065 Prospect of agricultural remote sensing research and application. *Journal of Remote Sensing* 20, 05 (2016), 748–767.
- 1066 [19] Michael D Johnson, William W Hsieh, Alex J Cannon, Andrew Davidson, and Frédéric Bédard. 2016. Crop Yield Forecasting on the Canadian
1067 Prairies by Remotely Sensed Vegetation Indices and Machine Learning Methods. *Agricultural and forest meteorology* 218 (2016), 74–84.
- 1068 [20] Liheng Zhong, Lina Hu, and Hang Zhou. 2019. Deep Learning Based Multi-Temporal Crop Classification. *Remote sensing of environment* 221 (2019),
1069 430–443.
- 1070 [21] Qi Yang, Liangsheng Shi, Jimye Han, Yuanyuan Zha, and Penghui Zhu. 2019. Deep Convolutional Neural Networks for Rice Grain Yield Estimation
1071 at the Ripening Stage Using UAV-based Remotely Sensed Images. *Field Crops Research* 235 (2019), 142–153.
- 1072 [22] Ulrich Weiss and Peter Biber. 2011. Plant Detection and Mapping for Agricultural Robots Using a 3D LIDAR Sensor. *Robotics and Autonomous
1073 Systems* 59, 5 (2011), 265–273. <https://doi.org/10.1016/j.robot.2011.02.011>
- 1074 [23] Huilin Tao, Haikuan Feng, Liangji Xu, Mengke Miao, Huiling Long, Jibo Yue, Zhenhai Li, Guijun Yang, Xiaodong Yang, and Lingling Fan. 2020.
1075 Estimation of Crop Growth Parameters Using UAV-Based Hyperspectral Remote Sensing Data. *Sensors* 20, 5 (2020), 1296. [https://doi.org/10.3390/s20051296](https://doi.org/10.3390/
1076 s20051296)
- 1077 [24] X. Zhou, H. B. Zheng, X. Q. Xu, J. Y. He, X. K. Ge, X. Yao, T. Cheng, Y. Zhu, W. X. Cao, and Y. C. Tian. 2017. Predicting Grain Yield in Rice Using
1078 Multi-Temporal Vegetation Indices from UAV-based Multispectral and Digital Imagery. *ISPRS Journal of Photogrammetry and Remote Sensing* 130
1079 (2017), 246–255. <https://doi.org/10.1016/j.isprsjprs.2017.05.003>
- 1080 [25] Maitiniyazi Maimaitijiang, Abduwasit Ghulam, Paheding Sidike, Sean Hartling, Matthew Maimaitiyiming, Kyle Peterson, Ethan Shavers, Jack
1081 Fishman, Jim Peterson, Suhas Kadam, Joel Burken, and Felix Fritsch. 2017. Unmanned Aerial System (UAS)-Based Phenotyping of Soybean
1082 Using Multi-Sensor Data Fusion and Extreme Learning Machine. *ISPRS Journal of Photogrammetry and Remote Sensing* 134 (2017), 43–58.
1083 <https://doi.org/10.1016/j.isprsjprs.2017.10.011>
- 1084 [26] Liang Wan, Haiyan Cen, Jiangpeng Zhu, Jiafei Zhang, Yueming Zhu, Dawei Sun, Xiaoyue Du, Li Zhai, Haiyong Weng, Yijian Li, Xiaoran
1085 Li, Yidan Bao, Jianyao Shou, and Yong He. 2020. Grain Yield Prediction of Rice Using Multi-Temporal UAV-based RGB and Multispectral
1086 Images and Model Transfer – a Case Study of Small Farmlands in the South of China. *Agricultural and Forest Meteorology* 291 (2020), 108096.
1087 <https://doi.org/10.1016/j.agrformet.2020.108096>
- 1088 [27] Jérôme G Fortin, François Anctil, Léon-Étienne Parent, and Martin A Bolinder. 2011. Site-Specific Early Season Potato Yield Forecast by Neural
1089 Network in Eastern Canada. *Precision agriculture* 12, 6 (2011), 905–923.
- 1090 [28] CA Campbell, RP Zentner, and PJ Johnson. 1988. Effect of Crop Rotation and Fertilization on the Quantitative Relationship between Spring Wheat
1091 Yield and Moisture Use in Southwestern Saskatchewan. *Canadian Journal of Soil Science* 68, 1 (1988), 1–16.
- 1092 [29] David L Ehret, Bernard D Hill, Tom Helmer, and Diane R Edwards. 2011. Neural Network Modeling of Greenhouse Tomato Yield, Growth and
Water Use from Automated Crop Monitoring Data. *Computers and electronics in agriculture* 79, 1 (2011), 82–89.
- 1093 [30] Snehal S Dahikar and Sandeep V Rode. 2014. Agricultural Crop Yield Prediction Using Artificial Neural Network Approach. *International journal of
1094 innovative research in electrical, electronics, instrumentation and control engineering* 2, 1 (2014), 683–686.

- [31] Monte R O'Neal, Bernard A Engel, Daniel R Ess, and Jane R Frankenberger. 2002. Neural Network Prediction of Maize Yield Using Alternative Data Coding Algorithms. (2002).
- [32] T Morimoto, Y Ouchi, M Shimizu, and MS Baloch. 2007. Dynamic Optimization of Watering Satsuma Mandarin Using Neural Networks and Genetic Algorithms. *Agricultural water management* 93, 1-2 (2007), 1–10.
- [33] Scott Drummond, Anupam Joshi, and Kenneth A Sudduth. 1998. Application of Neural Networks: Precision Farming. In *1998 IEEE International Joint Conference on Neural Networks Proceedings. IEEE World Congress on Computational Intelligence (Cat. No. 98CH36227)*, Vol. 1. IEEE, 211–215.
- [34] NR Kitchen, ST Drummond, ED Lund, KA Sudduth, and GW Buchleiter. 2003. Soil Electrical Conductivity and Topography Related to Yield for Three Contrasting Soil-Crop Systems. *Agronomy journal* 95, 3 (2003), 483–495.
- [35] Francisco M Padilla, Marisa Gallardo, M Teresa Peña-Fleitas, Romina De Souza, and Rodney B Thompson. 2018. Proximal Optical Sensors for Nitrogen Management of Vegetable Crops: A Review. *Sensors* 18, 7 (2018), 2083.
- [36] Saptarshi Sengupta, Sanchita Basak, Pallabi Saikia, Sayak Paul, Vasilios Tsalavoutis, Frederick Atiah, Vadlamani Ravi, and Alan Peters. 2020. A Review of Deep Learning with Special Emphasis on Architectures, Applications and Recent Trends. *Knowledge-Based Systems* 194 (2020), 105596.
- [37] Tadas Baltrušaitis, Chaitanya Ahuja, and Louis-Philippe Morency. 2019. Multimodal Machine Learning: A Survey and Taxonomy. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 41, 2 (2019), 423–443. <https://doi.org/10.1109/TPAMI.2018.2798607>
- [38] Paul Pu Liang, Amir Zadeh, and Louis-Philippe Morency. 2023. Foundations and Trends in Multimodal Machine Learning: Principles, Challenges, and Open Questions. arXiv:2209.03430 [cs]
- [39] Ben P Yuhas, Moise H Goldstein, and Terrence J Sejnowski. 1989. Integration of Acoustic and Visual Speech Signals Using Neural Networks. *IEEE Communications Magazine* 27, 11 (1989), 65–71.
- [40] Cees GM Snoek and Marcel Worring. 2005. Multimodal Video Indexing: A Review of the State-of-the-Art. *Multimedia tools and applications* 25, 1 (2005), 5–35.
- [41] Jing Chen, Chenhui Wang, Kejun Wang, Chaoqun Yin, Cong Zhao, Tao Xu, Xinyi Zhang, Ziqiang Huang, Meichen Liu, and Tao Yang. 2021. HEU Emotion: A Large-Scale Database for Multimodal Emotion Recognition in the Wild. *Neural Computing and Applications* 33, 14 (2021), 8669–8685.
- [42] Zhou Lei and Yiyong Huang. 2021. Video Captioning Based on Channel Soft Attention and Semantic Reconstructor. *Future Internet* 13, 2 (2021), 55.
- [43] Yu Long, Pengjie Tang, Hanli Wang, and Jian Yu. 2021. Improving Reasoning with Contrastive Visual Information for Visual Question Answering. *Electronics Letters* 57, 20 (2021), 758–760.
- [44] Rafael Souza, André Fernandes, Thiago SFX Teixeira, George Teodoro, and Renato Ferreira. 2021. Online Multimedia Retrieval on CPU-GPU Platforms with Adaptive Work Partition. *J. Parallel and Distrib. Comput.* 148 (2021), 31–45.
- [45] Amir Hossein Yazdavar, Mohammad Saeid Mahdavinejad, Goonmeet Bajaj, William Romine, Amit Sheth, Amir Hassan Monadjemi, Krishnaprasad Thirunarayan, John M Meddar, Annie Myers, Jyotishman Pathak, et al. 2020. Multimodal Mental Health Analysis in Social Media. *Plos one* 15, 4 (2020), e0226248.
- [46] Yu Huang, Chenzhuang Du, Zihui Xue, Xuanyao Chen, Hang Zhao, and Longbo Huang. 2021. What Makes Multi-modal Learning Better than Single (Provably). arXiv:2106.04538 [cs]
- [47] Chaoya Dang, Ying Liu, Hui Yue, JiaXin Qian, and Rong Zhu. 2021. Autumn Crop Yield Prediction Using Data-Driven Approaches: Support Vector Machines, Random Forest, and Deep Neural Network Methods. *Canadian Journal of Remote Sensing* 47, 2 (2021), 162–181.
- [48] Zheng Chu and Jiong Yu. 2020. An End-to-End Model for Rice Yield Prediction Using Deep Learning Fusion. *Computers and Electronics in Agriculture* 174 (2020), 105471. <https://doi.org/10.1016/j.compag.2020.105471>
- [49] Maitiniyazi Maimaitijiang, Vasit Sagan, Paheging Sidike, Sean Hartling, Flavio Esposito, and Felix B. Fritsch. 2020. Soybean Yield Prediction from UAV Using Multimodal Data Fusion and Deep Learning. *Remote Sensing of Environment* 237 (Feb. 2020), 111599. <https://doi.org/10.1016/j.rse.2019.111599>
- [50] Yucheng Zhao, Guangting Wang, Chuanxin Tang, Chong Luo, Wenjun Zeng, and Zheng-Jun Zha. 2021. A Battle of Network Structures: An Empirical Study of CNN, Transformer, and MLP. arXiv:2108.13002 [cs]
- [51] Jan GPW Clevers and Anatoly A Gitelson. 2013. Remote Estimation of Crop and Grass Chlorophyll and Nitrogen Content Using Red-Edge Bands on Sentinel-2 and -3. *International Journal of Applied Earth Observation and Geoinformation* 23 (2013), 344–351.
- [52] Aditya Prakash, Kashyap Chitta, and Andreas Geiger. 2021. Multi-Modal Fusion Transformer for End-to-End Autonomous Driving. arXiv:2104.09224 [cs]
- [53] Arsha Nagrani, Shan Yang, Anurag Arnab, Aren Jansen, Cordelia Schmid, and Chen Sun. [n. d.]. Attention Bottlenecks for Multimodal Fusion. ([n. d.]), 14.
- [54] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention Is All You Need. In *Advances in Neural Information Processing Systems*, I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett (Eds.), Vol. 30. Curran Associates, Inc.
- [55] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, and Dirk Weissenborn. 2021. An Image Is Worth 16x16 Words: Transformers for Image Recognition at Scale. arXiv:2010.11929 [cs]
- [56] Frederick N Fritsch and Ralph E Carlson. 1980. Monotone Piecewise Cubic Interpolation. *SIAM J. Numer. Anal.* 17, 2 (1980), 238–246.
- [57] Rutuja R. Patil and Sumit Kumar. 2022. Rice-Fusion: A Multimodality Data Fusion Framework for Rice Disease Diagnosis. *IEEE access : practical innovations, open solutions* 10 (2022), 5207–5222. <https://doi.org/10.1109/ACCESS.2022.3140815>
- [58] Rutuja Rajendra Patil and Sumit Kumar. 2022. Rice Transformer: A Novel Integrated Management System for Controlling Rice Diseases. *IEEE access : practical innovations, open solutions* 10 (2022), 87698–87714. <https://doi.org/10.1109/ACCESS.2022.3200688>

1145 [59] Zhengtao Li, Guokun Chen, and Tianxu Zhang. 2020. A CNN-Transformer Hybrid Approach for Crop Classification Using Multitemporal Multisensor
1146 Images. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 13 (2020), 847–858. <https://doi.org/10.1109/JSTARS.2020.2971763>

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1149 Received 20 February 2007; revised 12 March 2009; accepted 5 June 2009

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