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Forecasting of Grain Pile Temperature From Meteorological Factors Using Machine Learning

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ABSTRACT Food storage security is critical to the national economy and people's lives. The environmental parameters of a granary should be accurately monitored in order to provide a better preservation environment for food storage. In this paper, we use temperature sensors to measure and collect grain temperature data for a period of 423 days from a real world granary, and collect the corresponding meteorological data from China Meteorological Data Network. We propose to leverage meteorological data to predict the average temperature of the grain pile with machine learning algorithms: a support vector regression (SVR) approach and an adaptive boosting (AdaBoost) approach. We incorporate different kernel functions in the SVR model and choose the appropriate base-estimator and the number of estimators in the AdaBoost model. We then analyze the correlation between a large amount of historical data from the granary and the corresponding meteorological forecast data based on the Pearson correlation coefficient. We find that there are strong correlations between some meteorological factors. In order to eliminate redundant information, we reduce the dimension of data by principal components analysis (PCA), and compare the prediction models before and after PCA dimension reduction. The results show that the proposed approaches can achieve a high accuracy and the Adboost method after PCA dimension reduction achieves the best performance.

INDEX TERMS Food storage, temperature sensors, meteorological metrics, support vector regression, adaptive boosting, machine learning.

I. INTRODUCTION

The demand for food will be doubled by 2050 as population and social mobility increase [1]–[6]. Globally, more than 2 billion tons of food are harvested each year [7]. However, up to one third of the annual total global production of grain is lost because of poor post-harvest management. Lack of control over grain moisture content, high temperature, and insect infestation are the three most significant factors causing the loss. In fact, high grain moisture and temperature can provide favorable conditions for hot spot development, mold growth, and insect infestation [8]. Grain is still a physiologically active organism during storage, and is affected by the physical and biological environment. These internal and external factors are closely related to the safe storage of grain. With the development of science and technology, grain storage technology has been improved and food security has been better guaranteed. However, there are still many risk factors in the process of grain storage. The complex grain storage ecosystem is under the joint influence of the environment sub-ecosystem and the granary protection construction [9].

Grain temperature is an important indicator of grain conditions. Its detection and control technology are critical for

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the operation of grain warehouses (or, granary). In the entire grain detection system, detection of the temperature of stored grain is a relatively mature technology and has been widely used in national reserves [10]. In fact, the storage temperature is highly predictable when aggregating over thousands of granaries and storage parameters. Different from the developed countries, the present situation of grain storage in China is unique [8]. Recently, Yang et al. present a non-destructive and economic wheat moisture detection system with commodity WiFi, which can achieve high classification accuracy for both LOS and NLOS scenarios [11], [12].

To improve the accuracy of grain pile temperature forecasting, we focus on the issue of using the National Meteorological Information Center (NMIC) meteorological forecast to accurately predict grain pile temperature. In this paper, we first discuss the temperate measurement system for food storage. For a period of 423 days, we used temperature sensors to measure and collect of grain temperature data from the grain storage at the *No. 1 Warehouse* in the Xishan District of Kunming, Yunnan province, China. We also collect the corresponding meteorological data from China Meteorological Data Network. We provide an analysis of the correlation between a large amount of historical data from the granary and the corresponding meteorological data. We find that the surface temperature of grain pile has higher correlations with air temperature, relative humidity, and 0cm ground temperature, but a smaller correlation with air pressure. We propose to predict surface temperature of grain pile using multiple meteorological factors, aiming to achieve high predication accuracy.

In particular, we develop a support vector regression (SVR) approach [13]–[16] and an adaptive boosting (AdaBoost) approach to predict surface temperature of grain pile using multiple meteorological factors. In fact, because of some outliers recorded by temperature sensors, the raw data cannot be directly employed for the prediction model. We implement outlier detection and removal to delete bad data samples, and apply data normalization to all the sampled data to guarantee that the meteorological data and the surface temperature of grain pile have the same unit. Then, we leverage the calibrated meteorological data and grain temperature data to train the prediction model. Finally, we incorporate different kernel functions in the SVR model, and choose the appropriate base-estimator and the number of estimators in the AdaBoost model to predict the temperature of grain pile using meteorological data. We then analyze the correlation between a large amount of historical data from the granary and the corresponding meteorological forecast data based on the Pearson correlation coefficient. It is found that there is a strong correlation between some meteorological factors. In order to eliminate redundant information, we reduce the dimension of data by principal component analysis (PCA). We compare the prediction accuracy using different kernels in SVR model (such as the linear kernel function, the polynomial kernel function, and the Gaussian radial basis function (RBF) kernel) [17], [18] and Adaboost model with random forest regressor as base-estimator before and after PCA dimension reduction.

The main contributions of this paper are summarized below.

- To the best of our knowledge, this is the first work to use meteorological metrics to predict the average temperature of grain pile with machine learning.
- We employ temperature sensors to measure the grain temperature data from a real world grain storage for a period of 423 days, and collect meteorological data for the same region and time period. Then, we analyze the correlation between a large amount of historical granary data and the corresponding meteorological data based on the Pearson correlation coefficient.
- We implement outlier detection and data normalization for the raw meteorological and grain pile temperature data. We use different kernel functions with the SVR model and Adaboost model with random forest regressor to predict the average temperature of grain pile based on meteorological data. We compare the accuracy of grain surface temperature prediction using different kernel functions of SVR model and Adaboost model before and after PCA dimension reduction. The results show that the Adboost method with random forest regressor as base- estimator after principal components analysis achieves the best performance.

The remainder of this paper is organized as follows. Section II discusses the related work. The granary temperature measurement system is presented in Section III. Section IV describes grain temperature data measurement, collection process, and data preprocessing, and Section V discusses the SVR model and the Adaboost model. Section VI validates the performance of the proposed method using real world data. Section VII summarizes this paper.

II. RELATED WORK

The methods of temperature prediction for grain storage are mainly divided into two categories. The first one is based on the thermodynamic field theory. The basic thermodynamic laws and thermal conductivity differential equations are used to derive the temperature field distribution and its variation law of grain stack [19], [20]. Temperature and humidity are two important factors affecting grain storage status, which depict the change of temperature field of rice in silo during a grain storage period. Through validation, the optimum Chung-Pfost model of equilibrium humidity (EMC) is obtained, which provides support for predicting the change of temperature field and humidity field of rice during storage period. However, due to the neglect of the coupling effect of temperature field and humidity field, its prediction model needs to be further improved [21]. The coupled model of heat and moisture transfer is constructed by using the isothermal adsorption equation of grain moisture and the principle of local equilibrium of heat and mass, taking stored wheat and paddy as research objects [22]–[24]. The Fortan language programming is used to study the variation of the temperature field of the sorghum in the cylinder chamber with the temperature and humidity of the environment [25]. The model established by finite difference method can predict the changes of temperature and humidity in wheat grain heap during ventilation [26]. The work in [27]–[30] studies the mechanism of moisture and mass transfer in grain stacks, and constructs relevant mathematical models. On this basis, the distribution and variation of grain temperature and moisture under different storage conditions (mechanical ventilation and non-ventilation) are further studied by using computational fluid dynamics (CFD) simulation technology.

In addition, some scholars have studied the law of grain temperature change and mathematical model in high square warehouse [31]. The research shows that the mathematical model of temperature, warehouse temperature and "hot skin" temperature of grain stack are quadratic equation, and the mathematical model of "cold core" temperature is linear equation. It shows that the external temperature has a very obvious effect on warehouse temperature, and it has a great influence on "hot skin" area of grain stack. The effect of temperature in the region is also very obvious, but it has little effect on the "cold core" area of grain stack. The multi-point discrete characteristics of temperature data in large grain depots are used to find out the temperature distribution law, and the prediction method of temperature development trend at any point in the grain depot is discussed [32]–[34]. However, the temperature prediction model based on thermodynamic field theory relies on some assumptions about unsaturated wet porous media, and the model is fixed and pertinent, which is not applicable to the storage environment of different regions.

The second category is a data-driven solution that uses machine learning or data mining methods to build predictive models. An intelligent and optimized SVM model is proposed to predict the temperature change of grain stack during lateral ventilation. The grain situation prediction is realized by analyzing a large number of environmental data collected by the mining and monitoring center [35]. A temperature recognition model based on depth confidence network was established by using depth learning method to predict grain heap temperature [36]. Existing data-driven solutions do not take into account the characteristics of temperature gradient with time series. For temperature, increasing or decreasing temperature is a time-dependent gradient process, and its trend is very important for temperature prediction. The existing models have insufficient ability to deal with the time series correlation of temperature data, which leads to defects in temperature prediction. Many high-precision mathematical models and improved measurement systems are proposed to improve temperature monitoring and food storage management capabilities [37]–[39]. However, the work of grain temperature forecasting has been focused on time series models, which does not consider the effect of external meteorological factors. In fact, meteorological factors have been successfully utilized for accurate solar intensity forecasting [40], [41]. Our models can exploit meteorological factors for grain pile temperature forecasting, which is greatly different from the exiting works.

III. THE TEMPERATURE MEASUREMENT SYSTEM

To collect grain temperature data, we deploy a set of temperature sensors in the tall granary. Fig. 1 illustrates the tall flat granary architecture, which is divided into 10 rows from east to west, five regions from south to north, and four layers from top to bottom. Then 200 temperature sensors are deployed in this granary, and the sensors are encapsulated in cables and the cables are inserted into the grain pile at certain places. In the tall square granary, the temperature sensor layout principle is that the distance between the horizontal and horizontal temperature measuring cables should be no more than 5 m, the distance between the vertical cables should be no more than 2 m, and distance from the cables to the grain surface, granary bottom, and granary wall should within 0.3 m to 0.5 m.

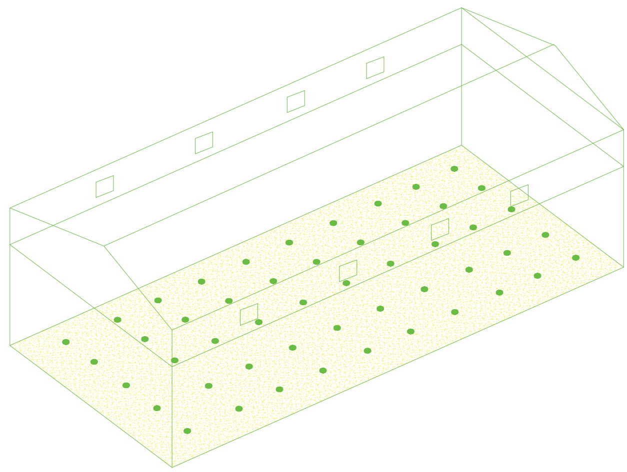


FIGURE 1. The tall flat granary model.

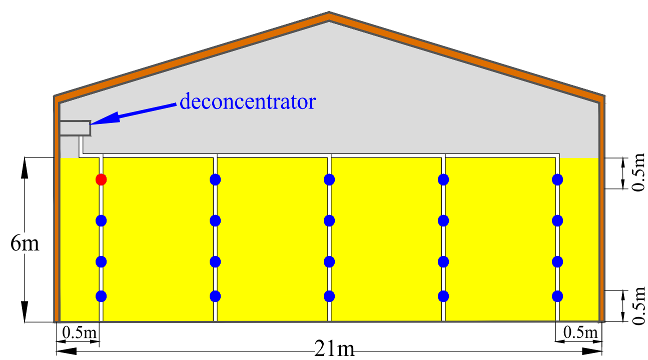


FIGURE 2. The cross section view of a granary.

Fig. 2 presents a cross-sectional view of the granary. The temperature monitoring system generally includes temperature sensors, temperature measuring cables, and a computer monitoring terminal. Each vertical line in the figure represents a cable, and four temperature sensors are encapsulated

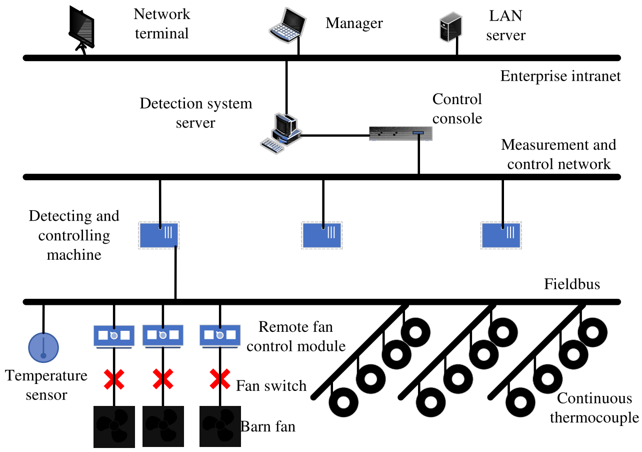


FIGURE 3. **Structure of the grain condition measurement and control system.**

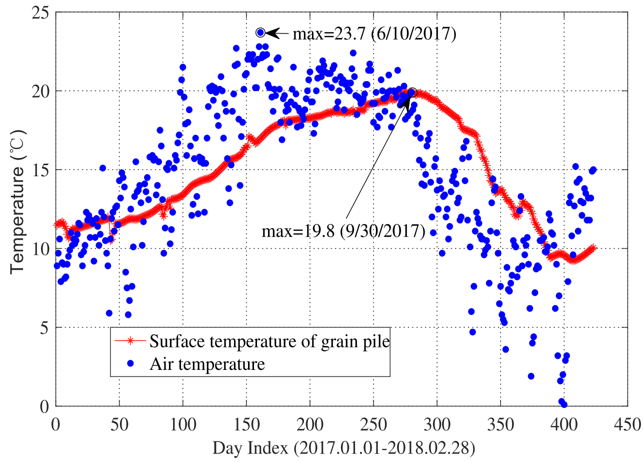


FIGURE 4. **Average temperature of the first layer of the stored grain pile and air temperature over days.**

in each cable. To monitor the abnormal change of temperature in the early stage of grain damage, the distance between the temperature measuring cables should be less than 0.5 m. Therefore, a large number of cables are needed, which would be hard to deploy (i.e., buried in the gain pile at precise locations) and lead to high measurement cost. Fig. 3 is the structural diagram of the grain condition measurement and control system in the granary. The computer sends test commands to the extension, receives test data from the extension, and then processes the receiving data. The extension receives the computer command, detects temperature data, and sends the results to the computer. The digital sensor is encapsulated inside the cable and laid inside the barn. Both digital temperature sensors and humidity sensors use a wire bus communication protocol to report sensory data.

The inspection time of grain temperature is preferably from 9 am to 10 am every day, when the temperature is close to the daily average temperature. While checking the temperature of the grain, we should also check the temperature inside the granary and the temperature outside the granary for analysis and comparison. All data is sampled once a day.

IV. DATA COLLECTING AND PREPROCESSING

A. DATA COLLECTING

We measured and collected the grain temperature data of the grain storage in the *No. 1 Warehouse* at Xishan District of Kunming, Yunnan, China for a period of 423 days since January 1, 2017. Then we downloaded the meteorological data of the corresponding region for the corresponding period of time from China Meteorological Data Network (http://data.cma.cn/). The meteorological metrics include air pressure, air temperature, relative humidity, precipitation, evaporation, wind speed, sunshine duration and 0 cm ground surface temperature. The temperature samples of grain pile are recorded by deployed sensors at 9 am every day. Then, we measure how the surface temperature of the grain pile changes with the meteorological variables and how these variables are influenced by each other.

Fig. 4 presents the surface temperature of the grain pile and the air temperature of the period. We find that the surface temperature of the grain pile and the air temperature are positively correlated. In other words, the temperature of the first layer of the stored grain pile becomes higher or smaller as the air temperature increases or decreases. However, there are other factors that also contribute to the surface temperature of the grain pile reading, since the surface temperature of the grain pile has been delayed for several months compared to the air temperature. It is noticed the highest air temperature was in June, while the highest temperature of the first layer of the grain pile was in September.

In Fig. 5, we can see that air temperature (subplot (a)), 0 cm ground surface temperature (subplot (b)), and relative humidity (subplot (c)) are all positively correlated with the surface temperature of the grain pile, especially at higher values. If the air temperature, 0 cm ground surface temperature, or relative humidity become larger, the surface temperature of the grain pile will likely increase too.

To study the correlation between the average temperature of the first layer of the stored grain pile and the meteorological metrics, we compute the Pearson correlation coefficients between pair of the factors. Table 1 provides the Pearson product moment correlation coefficients for all the meteorological variables and the surface temperature of grain pile. The higher the absolute value of the correlation coefficient, the higher the correlation between the two parameters. From Table 1, we find that the surface temperature of grain pile has higher correlations with air temperature, relative humidity, 0 cm ground temperature, but with a smaller correlation with air pressure. Based on this study, we develop an SVR algorithm and an Adaboost algorithm to predict the surface temperature of grain pile using multiple meteorological parameters, which is discussed in the following section.

In this section, SVR with different kernels and Adaboost with random forest regressor as the base-estimator are utilized to predict the surface temperature of grain storage.

TABLE 1. Correlation matrix showing correlation between different forecast parameters.

	Airpre	Airtem	Relhum	Preci	Eva	Windspeed	Sunduration	0cmgrotem	graintem
Air pressure	1.000	-0.499	0.13	-0.119	-0.241	-0.099	-0.175	-0.436	-0.088
Air temperature	-0.499	1.000	-0.005	0.228	0.125	-0.070	0.135	0.953	0.706
Relative humidity	0.135	-0.005	1.000	0.394	-0.788	-0.633	-0.715	-0.091	0.494
Precipitation	-0.119	0.228	0.394	1.000	-0.215	-0.217	-0.403	0.152	0.350
Evaporation	-0.241	0.125	-0.788	-0.215	1.000	0.539	0.566	0.213	-0.339
Wind speed	-0.099	-0.070	-0.633	-0.217	0.539	1.000	0.362	-0.039	-0.396
Sunshine duration	-0.175	0.135	-0.715	-0.403	0.566	0.362	1.000	0.221	-0.260
0 cm ground temperature	-0.436	0.953	-0.091	0.152	0.213	-0.039	0.221	1.000	0.623
Surface temperature of grain pile	-0.088	0.706	0.494	0.350	-0.339	-0.396	-0.260	0.623	1.000

B. DATA PREPROCESSING

Due to some outliers recorded by the sensors, the data units are inconsistent; thus the raw data cannot be directly used by the prediction models. Therefore, the data must be processed first before prediction. The data processing module includes outlier detection and data normalization, which are discussed in the following.

- *Outlier detection*: Some abnormal values are reported by temperature sensors. Outlier detection is used to recognize bad data values, which should be removed from the raw data. In this paper, we leverage the *Pauta criterion* method and the *linear trend at point* method to get rid of outliers. The outlier detection method is as follows.

  Step 1: Let X_i, $i = 1, 2, ..., n$, be the ith value of meteorological metrics or the average temperature of the first layer of grain pile. We calculate the arithmetic mean value as
$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i. \tag{1}$$

  Step 2: We then obtain the residual e_i as in (2) and the standard deviation σ of the meteorological metrics or the average temperature of the first layer of grain pile as in (3).
$$e_i = X_i - \bar{X}, \quad i = 1, 2, ..., n \tag{2}$$
$$\sigma = \sqrt{\tfrac{1}{n-1}\textstyle\sum_{i=1}^{n}(X_i - \bar{X})^2}. \tag{3}$$

  Step 3: For all X_i, $i = 1, 2, ..., n$, if $|e_i| > 3\sigma$, we consider X_i as an abnormal value and replace it with the arithmetic mean value $\bar{X}$.

  Step 4: Repeat the above three steps till all the X_is are processed.
- Data normalization: To guarantee that the meteorological data and the surface temperature of grain pile have the same unit, we choose the *zero-mean normalization* method to normalize all sampled data. The normalized value Z_i is computed as
$$Z_i = \frac{1}{\sigma}\cdot(X_i - \bar{X}), \; i = 1, 2, ..., n. \tag{4}$$

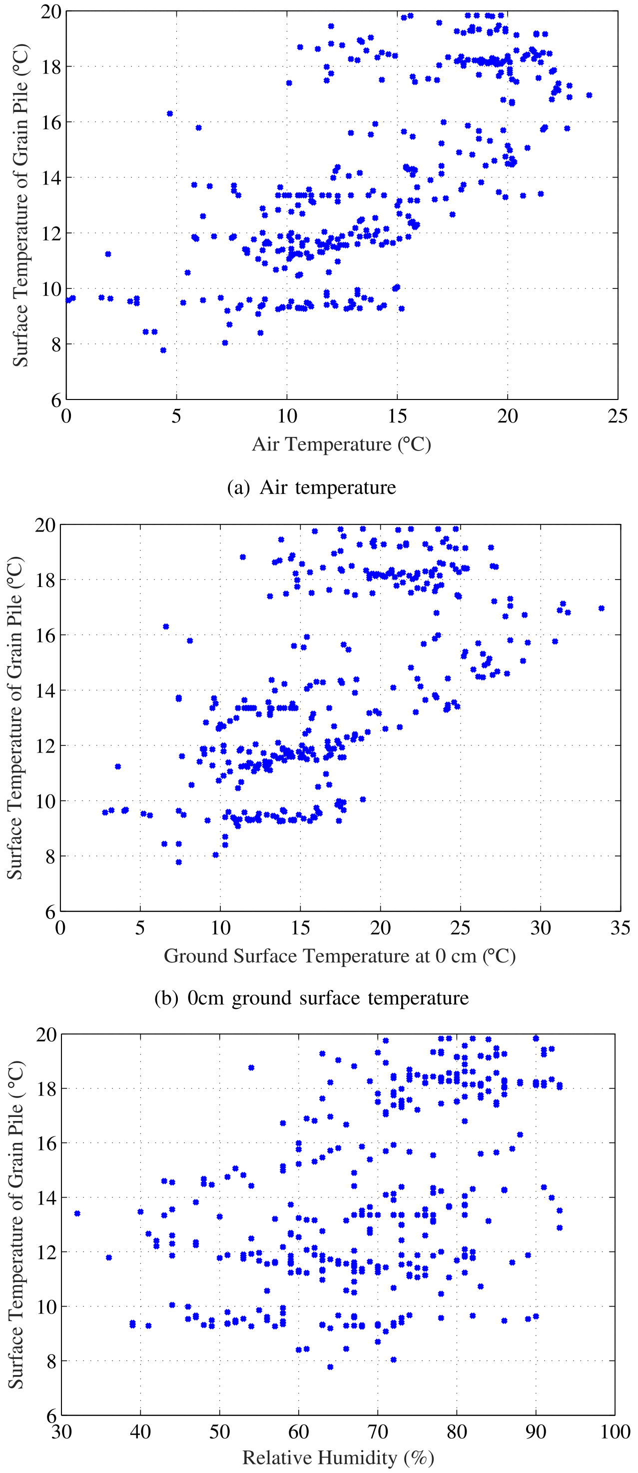
After data preprocessing, the training samples are
$$\mathcal{T} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), ..., (\mathbf{x}_n, y_n)\}, \tag{5}$$
where $\mathbf{x}_i$ is a vector of eight calibrated meteorological metrics in the ith sample, and y_i represents the calibrated average surface temperature of grain pile in the ith sample.

V. FORECASTING MODELS FOR GRAIN PILE SURFACE TEMPERATURE

A. SUPPORT VECTOR REGRESSION (SVR)

The SVR model is utilized to learn a function $f(\mathbf{x})$, which is close to the gain surface temperature y as much as possible [13]. The function is defined by
$$f(\mathbf{x}) = \boldsymbol{w}^T \cdot \phi(\mathbf{x}) + b, \tag{6}$$
where $\boldsymbol{w}$ and b are the parameters to be determined, and $\phi(\cdot)$ is a generic function. A deviation ε is used to evaluate the loss between the output $f(\mathbf{x})$ of the model and the true grain surface temperature y. In other words, when $|f(\mathbf{x}) - y| < \varepsilon$, the prediction result can be considered to be accurate.

The SVR problem can be formulated as follows.
$$\min_{\boldsymbol{w},b} \; \frac{1}{2}\|\boldsymbol{w}\|^2 + C\cdot\sum_{i=1}^{n} l_\varepsilon\left(f\left(\mathbf{x}_i\right) - y_i\right), \tag{7}$$
where C is a regularization constant and $l_\varepsilon(\cdot)$ is an insensitive loss function of ε. Adding a slack variable to the loss metric, problem in (7) can be transformed into a minimization problem (8) as follows.
$$\min_{\boldsymbol{w},b,\xi_i,\hat{\xi}_i} \; \frac{1}{2}\|\boldsymbol{w}\|^2 + C\cdot\sum_{i=1}^{n}\left(\xi_i + \hat{\xi}_i\right) \tag{8}$$
$$s.t.\, f\left(\mathbf{x}_i\right) - y_i \le \xi_i + \varepsilon, \; i = 1, 2, ..., n \tag{9}$$
$$y_i - f\left(\mathbf{x}_i\right) \le \hat{\xi}_i + \varepsilon, \; i = 1, 2, ..., n \tag{10}$$
$$\xi_i \ge 0, \hat{\xi}_i \ge 0, \; i = 1, 2, ..., n, \tag{11}$$
where ξ_i and $\hat{\xi}_i$ are slack variables. To solve problem (8), we first obtain the following Lagrange function using the Lagrange multiplier method, defined as follows.
$$\begin{aligned} &L(\boldsymbol{w}, b, \alpha, \hat{\alpha}, \xi, \hat{\xi}, \mu, \hat{\mu}) \\ &= \frac{1}{2}\|\boldsymbol{w}\|^2 + C\cdot\sum_{i=1}^{n}\left(\xi_i + \hat{\xi}_i\right) - \sum_{i=1}^{n}\mu_i\cdot\xi_i \\ &\quad - \sum_{i=1}^{n}\hat{\mu}_i\cdot\hat{\xi}_i + \sum_{i=1}^{n}\alpha_i\cdot\left(f\left(\mathbf{x}_i\right) - y_i - \varepsilon - \hat{\xi}_i\right) \\ &\quad + \sum_{i=1}^{n}\hat{\alpha}_i\cdot\left(y_i - f\left(\mathbf{x}_i\right) - \varepsilon - \xi_i\right), \end{aligned} \tag{12}$$
where μ, $\hat{\mu}$, α, and $\hat{\alpha}$ are Lagrange multipliers. Applying the duality theory, the average temperature and humidity of the



(a) Air temperature

(b) 0cm ground surface temperature

(c) Relative humidity

FIGURE 5. Average temperature of the first layer of the stored grain pile generally increases with increased (a) air temperature, (b) 0 cm ground surface temperature, and (c) relative humidity. (a) Air temperature. (b) 0cm ground surface temperature. (c) Relative humidity.

grain surface can be estimated as

$$f(\mathbf{x}) = \sum_{i=1}^{n} \left(\alpha_i - \hat{\alpha}_i\right) \cdot \phi\left(\mathbf{x}_i\right)^T \cdot \phi\left(\mathbf{x}\right) + b. \tag{13}$$

B. ADAPTIVE BOOSTING REGRESSION (ADABOOST)

In addition to SVM, we also consider Adaboost model for grain pile temperature forecasting from meteorological factors, which is one of the most famous algorithms in the boosting family. The working mechanism of boosting algorithm is as follows: firstly, a basic learner is trained from the initial training set and the distribution of training samples is adjusted according to the performance of the basic learner, and then the next basic learner is trained based on the adjusted sample distribution. The above steps are repeated until the number of basic learners reaches the predetermined value. All the basic learners are combined according to the combination strategy to obtain the final strong learner. Basic learners are weak learners which are only better than random guesses, such as a simple decision tree. The reason for using weak learners instead of strong learners is that it is often much easier to find a weak learner than a strong learner. Boosting method is to start from the weak learner and build a strong learner through repeated learning [42]–[44]. In particular, the core idea of Adaboost is to select a base estimator, fit a series of weak estimators on a series of data, and according to the accuracy of these estimators, provide each estimator a weight, then multiply all estimators by their respective weights and add them together to obtain the final prediction. The basic principle of the Adaboost algorithm is shown in Fig. 6.

The input of Adaboost model is the training samples $\mathcal{T}$, base learning algorithms $\mathcal{L}$ and the number of base learners M. The process is as follows:

Step 1: The weight distribution of initial training samples is provided,

$$D_1 = (w_{11}, \ldots, w_{1i}, \ldots, w_{1n}), \quad w_{1i} = \frac{1}{n}. \tag{14}$$

Step 2: For iteration round $t = 1, 2, \ldots, M$, we train a base learner using training data set with current distribution D_t

$$h_t = \mathcal{L}(D, D_t). \tag{15}$$

Then, we compute the maximum sample error on the training set

$$E_t = \max |y_i - h_t(x_i)|, \quad i = 1, 2, \ldots, n. \tag{16}$$

We can then obtain the relative error of each sample e_{ti}, i.e.,

$$e_{ti} = \frac{|y_i - h_t(x_i)|}{E_t}. \tag{17}$$

In addition, the regression error rate of the base learner h_t on training set is

$$\varepsilon_t = \sum_{i=1}^{n} w_{ti} \cdot e_{ti}. \tag{18}$$

The weight coefficient α_t of the base learner h_t is

$$\alpha_t = \frac{\varepsilon_t}{1 - \varepsilon_t}. \tag{19}$$

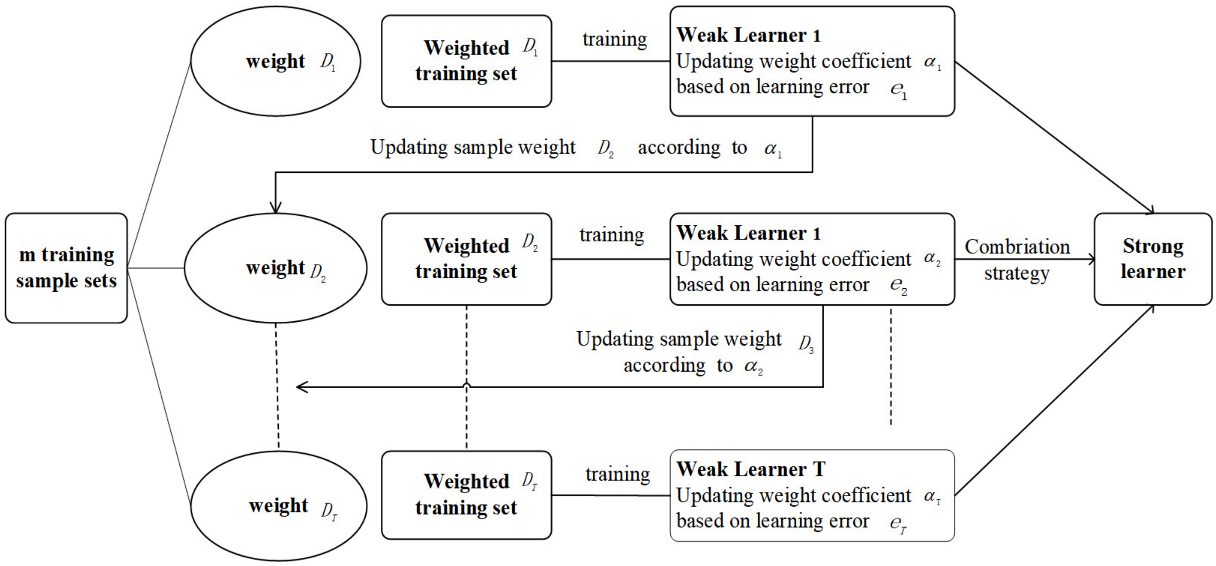


FIGURE 6. Basic principle diagram of the Adaboost algorithm.

Then, we update the sample distribution $D_{t+1} = (w_{t+1,1}, \ldots, w_{t+1,i}, \ldots, w_{t+1,n})$ of training set, that is,

$$w_{t+1,i} = \frac{w_{ti}}{z_t} \cdot \alpha_t^{1-e_{ti}}, \tag{20}$$

where z_t is the normalization factor, which is defined by

$$z_t = \sum_{i=1}^{n} \left(w_{ti} \cdot \alpha_t^{1-e_{ti}} \right). \tag{21}$$

Step 3: Finally, the basic learners are combined to obtain the final strong learner

$$H(x) = \sum_{t=1}^{M} \ln \left(\frac{1}{\alpha_t} \right) \cdot g(x), \tag{22}$$

where $g(x)$ is the median of all $\alpha_t \cdot h_t(x)$.

VI. PERFORMANCE EVALUATION

In this section, we evaluate the performance of our proposed approach using real measurement data: the temperature data of grain storage at the *No. 1 Warehouse* in the Xishan District of Kunming, Yunnan, China for a period of 423 days. The meteorological data of the corresponding region and period are obtained from the China Meteorological Data Network (http://data.cma.cn/).

A. PERFORMANCE EVALUATION OF SVR WITH DIFFERENT KERNEL FUNCTIONS

Firstly, we leverage SVR to predict the surface temperature of grain piles based on meteorological metric data. Because of the poor thermal conductivity of the grain kernel itself and the thermal insulation of the silo wall of the granary, some samples cannot be linearly divided in the two dimensional space. Thus, we consider a *kernel function* to map the samples to a higher dimensional space, which can achieve a better separability performance. Under Python 2.7 environment, the training process of regression model is as follows: 8 meteorological factors are taken as independent variables, average temperature of grain stack surface as dependent variables, and independent variables and dependent variables are as input of SVR. The mapping relationship between X and Y is constructed by machine learning self-learning. In order to ensure that the same training set and test set are segmented in each run, the same random number seeds are set [13].

In this paper, the linear kernel function, the polynomial kernel function, and the Gaussian RBF kernel function are used to predict the average temperature of the first layer of the stored grain pile [45]. We discuss the detailed experimental results in the following.

The linear kernel function is defined as follows.

$$k(\mathbf{x}, \mathbf{x}_i) = \mathbf{x} \cdot \mathbf{x}_i. \tag{23}$$

We use a linear kernel for the SVR model, where the dimension of the feature space is the same as the input space. It requires fewer parameters and also achieves a faster computational speed. The collected meteorological data of 423 days and the corresponding average temperature of the first layer of grain pile are used as data samples. The temperature of the first layer of grain pile per day corresponds to eight metrics of meteorology at the same time. We randomly select 80% of the samples as the training set, and the remaining 20% of the samples as the test set. The results of predicting the average temperature of the first layer of grain pile using the linear kernel function are presented in Fig. 7.

The polynomial kernel function is defined as follows.

$$k(\mathbf{x}, \mathbf{x}_i) = ((\mathbf{x} \cdot \mathbf{x}_i) + 1)^d, \tag{24}$$

where d represents the order of the polynomial. In our experiment, we set $d = 2$, which achieves a good performance.

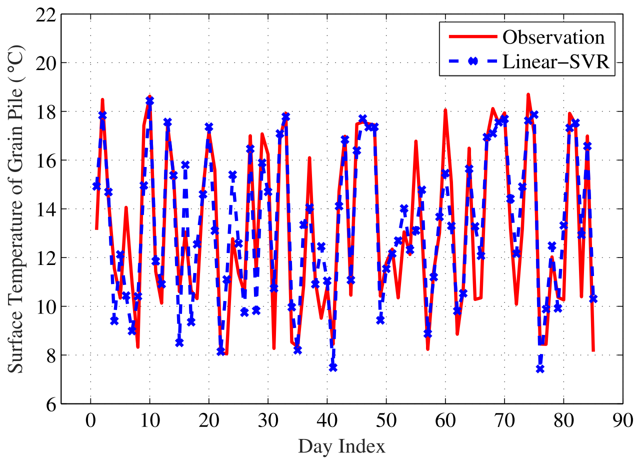


FIGURE 7. Observation and predicted average temperature of the first layer of the stored grain pile using the linear kernel function.

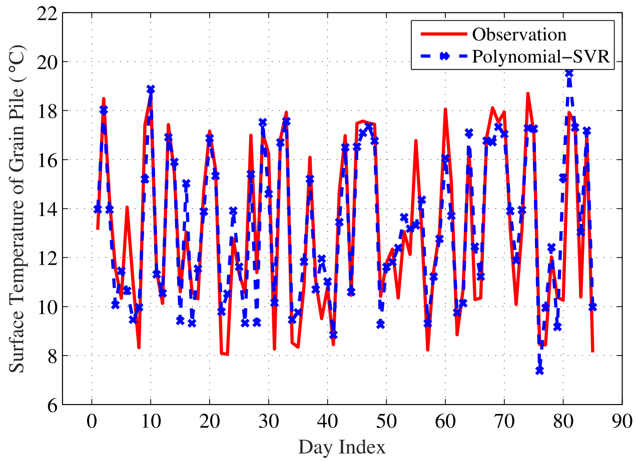


FIGURE 8. Observed and predicted average temperature of the first layer of the stored grain pile using the polynomial kernel function.

Due to the ventilation and food turning operations during grain storage, the sample size collected within a time period is limited and the feature dimension is relatively small. The polynomial kernel function can map the low-dimensional input space to a high-dimensional feature space, but the corresponding computational complexity is higher. The results of predicting the average temperature of the first layer of grain pile obtained by the polynomial kernel function are shown in Fig. 8.

The Gaussian RBF kernel function is defined as follows.

$$k\left(\mathbf{x}, \mathbf{x}_i\right) = \exp\left(-\frac{\|\mathbf{x}-\mathbf{x}_i\|^2}{2\delta^2}\right). \tag{25}$$

where δ is the parameter of the Gaussian RBF. This is a locally strong kernel function that maps samples into a higher dimensional space. It can achieve a good performance for both large and small samples, and requires fewer parameters than the polynomial kernel function. The results of predicting the average temperature of the first layer of grain pile using the Gaussian RBF kernel function are shown in Fig. 9.

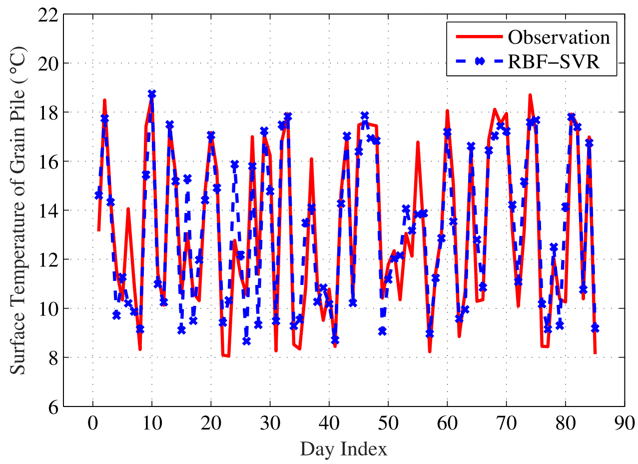


FIGURE 9. Observed and predicted average temperature of the first layer of the stored grain pile using RBF.

B. PERFORMANCE EVALUATION OF ADABOOST WITH RANDOM FOREST REGRESSOR AS BASE-ESTIMATOR

The advantage of Adaboost is that various regression models can be used to construct weak learners, and it is not easy to appear over-fitting phenomenon. Its disadvantage is that it is sensitive to abnormal samples. Abnormal samples may have larger weight in iteration, which affects the prediction accuracy of strong learners. Fortunately, we preprocess the abnormal samples using outlier detection and data normalization, which just overcomes the shortcomings of Adaboost. Adaboost algorithm itself is a lifting algorithm. It can use any learner as a base learner. Generally speaking, the most widely used weak Adaboost learners are decision tree and neural network. For decision tree, Adaboost classification uses CART classification tree, while Adaboost regression uses CART regression tree. According to the predictive performance of SVR in section VI-A, we first select the SVR as the base learner. Under the same number of basic learners and learning rate, the linear kernel function, polynomial kernel function and Gauss radial basis function of SVR are trained respectively. It is found that when the polynomial kernel function of SVR and the Gauss radial basis function are used as the base learners, the calculation time is too long to be applicable. Then we choose the linear kernel function of SVR and the random forest regressor as the base learner. The results show that the prediction error of using random forest regressor as the base learner is small. In addition, because the high accuracy and good anti-noise ability of random forest, it is used as the basic learner of AdaBoost regression in this paper. In order to prevent over-fitting, a regularization term v is usually added to the Adaboost algorithm, which is often referred as a learning rate. For the same training set, smaller v means more iterations of weak learners. The step size and the maximum number of iterations are usually used together to determine the fitting effect of the algorithm.

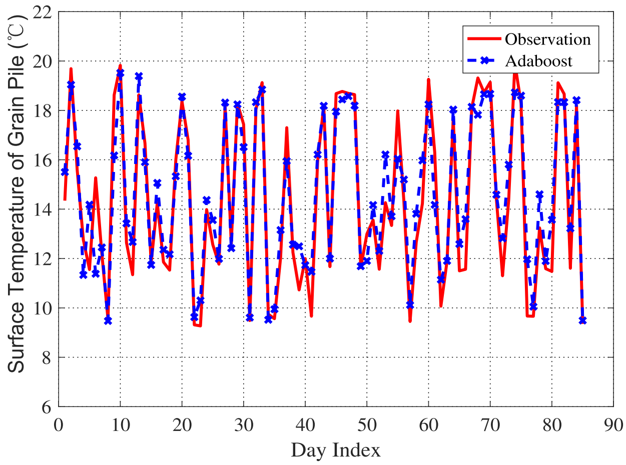


FIGURE 10. **Observed and predicted average temperature of the first layer of the stored grain pile using Adaboost.**

Under Python 2.7 environment, the training process of regression model is as follows: 8 meteorological factors are taken as independent variables, average temperature of grain stack surface as dependent variables, and independent variables and dependent variables are as input of Adaboost regression. In order to ensure that the same training set and test set are segmented in each run, the same random number seeds are set [13]. If the number of base learners M is too small, it is easy to cause under-fitting, but if it is too large, it will cause a large amount of calculation. When M reaches a certain number, the model upgrade obtained by increasing the value of M will be very small, so a moderate M value is generally chosen. In our Adaboost model, the number of base learners is 11, and the learning rate is 0.001. The collected meteorological data of 423 days and the corresponding average temperature of the first layer of grain pile are used as data samples. The temperature of the first layer of grain pile per day corresponds to eight metrics of meteorology at the same time. We randomly select 80% of the samples as the training set, and the remaining 20% of the samples as the test set. The results of predicting the average temperature of the first layer of grain pile using the Adaboost algorithm with random forest regressor as base estimator is shown in Fig. 10. We can notice that the proposed Adaboost algorithm has a better regression performance compared with SVR based methods.

C. ELIMINATING REDUNDANT INFORMATION

As we show in Table 1, the correlation coefficients between some meteorological factors are relatively large, which indicates that there are strong correlations among these factors such as air temperature and ground temperature, relative humidity and evaporation. In Fig. 11, we can see that air temperature and air pressure (subplot (a)), 0 cm ground surface temperature and air pressure(subplot (b)) show negative correlation with each other. 0 cm ground surface temperature and air temperature (subplot (c)) show strong positive correlation with each other. As a result, our regression models

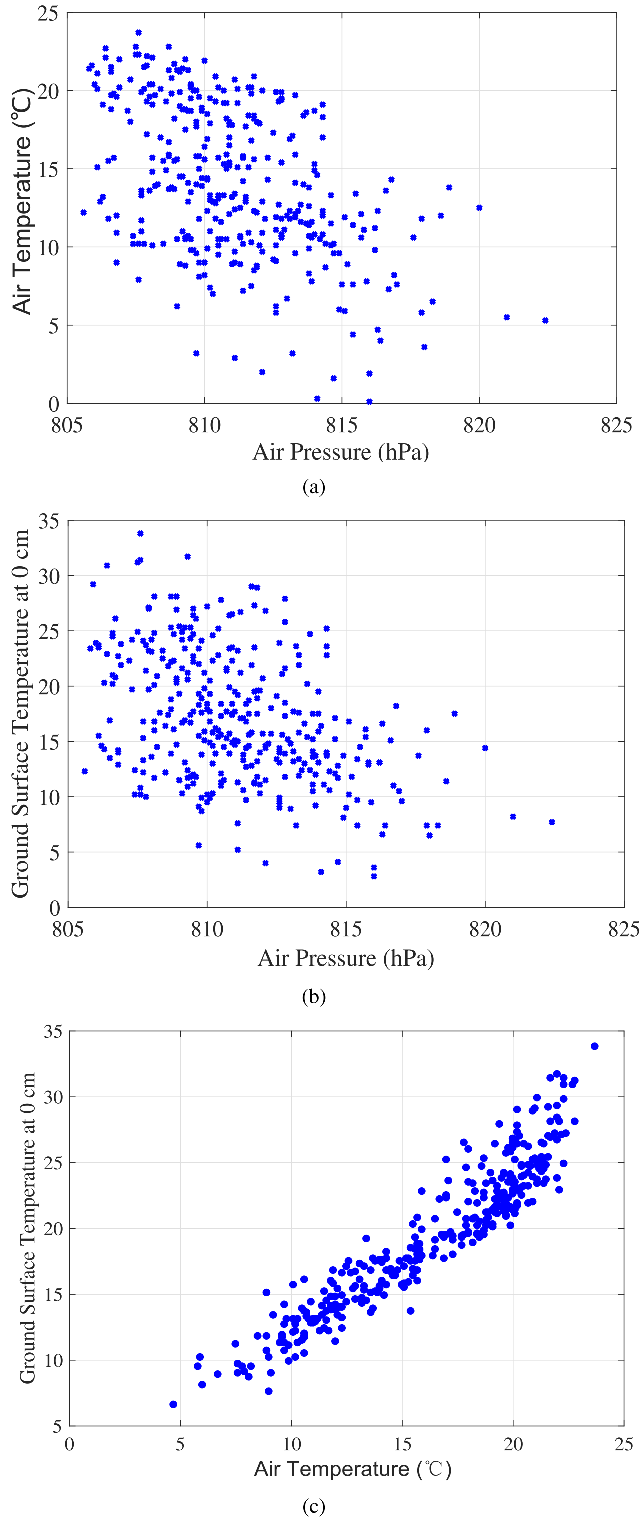


FIGURE 11. **The relationship of meteorological factors.**

contain redundant information, which often decreases the prediction accuracy of each model. PCA is a popular method for removing redundant information from an input dataset, thereby reducing its dimensionality [46]–[48]. Thus, we use the PCA method to remove redundant information from our

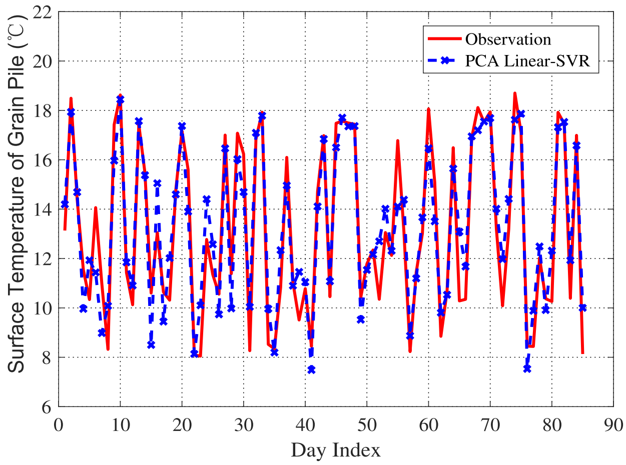


FIGURE 12. Observed and predicted average temperature of the first layer of the stored grain pile using the linear kernel function after PCA.

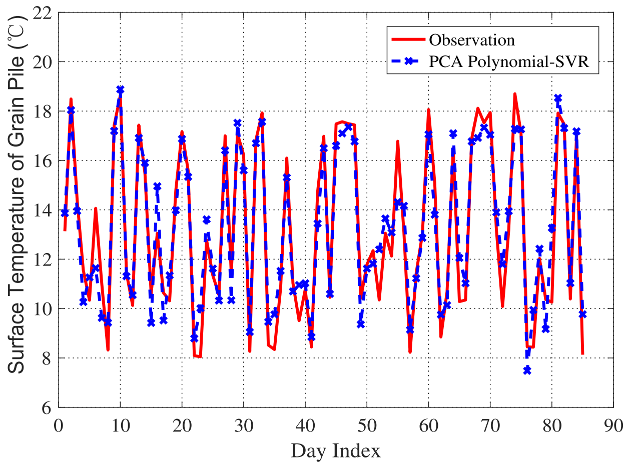


FIGURE 13. Observed and predicted average temperature of the first layer of the stored grain pile using the polynomial kernel function after PCA.

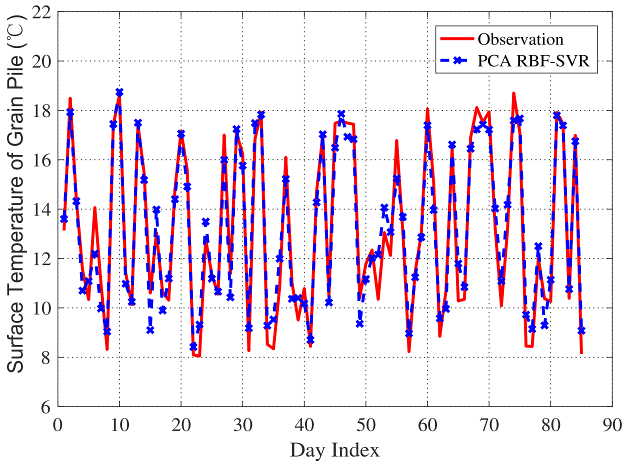


FIGURE 14. Observed and predicted average temperature of the first layer of the stored grain pile using RBF after PCA.

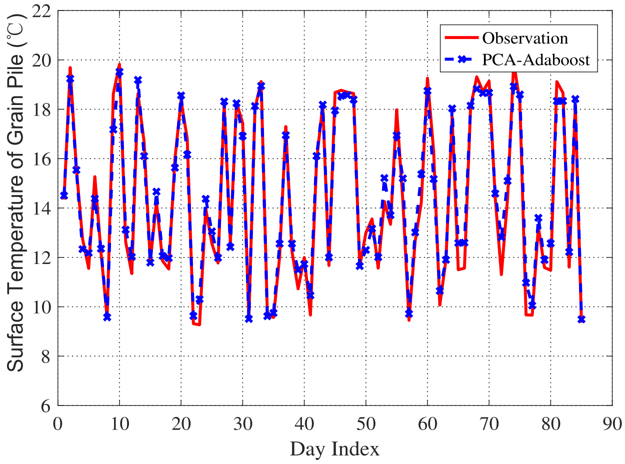


FIGURE 15. Observed and predicted average temperature of the first layer of the stored grain pile using Adaboost after PCA.

feature dataset. The PCA algorithm uses an orthogonal transformation to convert a set of potentially correlated input variables into a set of uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables.

We choose the first seven (highest) eigenvalues and run the regression method on the reduced feature set. The results show that the prediction model is better than the full feature set when PCA is reduced to 7 dimensions. In Fig. 15, the Adaboost algorithm with random forest as base learner can achieve a minimum RMS-Error of 1.26 after PCA and of 1.79 before PCA dimensionality reduction, respectively. In Fig. 14, the RBF kernel can obtain a RMS-Error of 3.94 after PCA and of 4.45 before PCA dimensionality reduction, respectively. In Fig. 13, the polynomial kernel can have a RMS-Error of 4.48 after PCA and of 4.69 before PCA dimensionality reduction, respectively. In Fig. 12, the linear kernel can get a RMS-Error of 4.873 after PCA and of 5.249 before PCA dimensionality reduction, respectively.

We also ran experiments for reducing the dimensionality of the feature set from 7 to 6. However, we found that all three SVM regression techniques performed worse compared to the 7-dimensional feature set. The performance degradation is that the information of the additional reduction in dimensionality is not redundant.

D. COMPARISON

In order to quantitatively measure the prediction performance of the SVR method using different kernel functions and the Adaboost method with random forest regressor as base estimator, the root mean square error (RMSE) is used as the evaluation criteria. In addition, the execution time of the algorithm is taken as another criterion for evaluation. Using the different kernel functions in the SVR model and random forest regressor as base estimator in the Adaboost model to predict the average temperature of the first layer of grain pile, the RMSE results are presented in Fig. 16. It can be seen that all the three schemes are quite accurate, while Adaboost method with random forest regressor as base

TABLE 2. The RMSES and the execution time of different prediction models.

	Dimensions	SVR-linear	SVR-polynomial	SVR-RBF	Adaboost
RMSE	Full Feature Set	5.249	4.69	4.45	1.79
RMSE	PCA 7 Dimensions	4.873	4.48	3.94	1.26
Execution Time (s)	Full Feature Set	4.91	2.63	0.023	1.73
Execution Time (s)	PCA 7 Dimensions	4.83	2.12	0.021	1.55

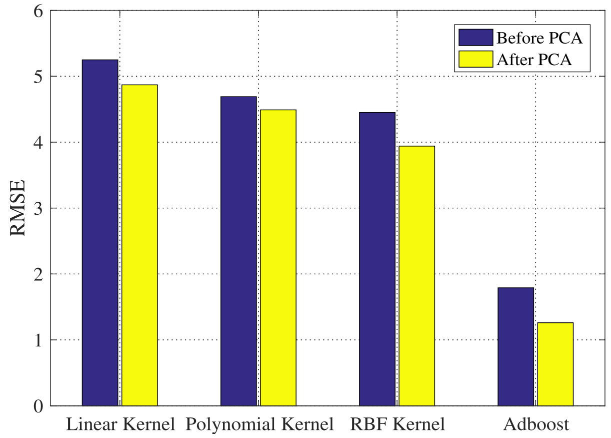


FIGURE 16. RMSEs achieved by SVR using different kernel functions and Adaboost with random forest regressor as base estimator.

estimator achieves the smallest RMSE result. The polynomial kernel function achieves a 10.50% reduction over the linear kernel function. The Gaussian RBF kernel function achieves a reduction of 15.08% and 5.12% over the linear and polynomial kernel function, respectively. The Adaboost method with random forest regressor as base estimator achieves a reduction of 65%, 61%, and 59% over the linear kernel function, polynomial kernel function and Gaussian RBF kernel function in SVR, respectively. Although the complexity of the model has not changed, the number of features is reduced after PCA dimensionality reduction. As a result, the execution time is reduced and it reaches the minimum value when RBF kernel function is used. The RMSEs and the execution time of different prediction models are shown in Table 2.

VII. CONCLUSION

In this paper, we leveraged an SVR approach and an Adaboost approach to predict the average temperature of the first layer of the stored grain pile using meteorological metrics. Due to the poor thermal conductivity of the grain kernel itself and the thermal insulation properties of the granary wall, the average temperature of the first layer is usually delayed by a certain amount of time than the outside air temperature. Among eight factors of meteorology, there are three factors, including air temperature, 0cm ground temperature, and relative humidity, that have a greater impact on the average temperature of the first layer. We used different kernel functions in the SVR model and chose the appropriate base-estimator and the number of estimators in the AdaBoost model. Grain temperature data measured from a real granary and the corresponding meteorological data were used in our study. The results demonstrated that the Adboost method after PCA dimension reduction can achieve a minimum RMS-Error of 1.26, which is better than kernel based SVM methods.

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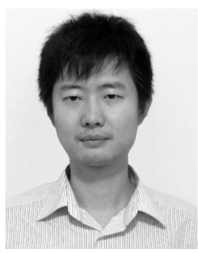

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