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An IoT Tree Health Indexing Method Using Heterogeneous Neural Network

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ABSTRACT

Urban trees provide essential ecosystem services on regulating temperature and humidity, filtering urban pollutants, and improving air quality. However, the increasing number of urban trees put pressure on maintenance and public safety. The total compensatory value of the trees, consisting of inspection, maintenance, and settlement of tree damages, is more than $2 trillion USD. At this point in time, there is no known research on manifesting guidance on automated tree health assessment. The Internet-of-Things (IoT) proliferates the deployment of wireless sensors and networks. A concept of the IoT trees is raised to implement various sensors on the trees for automated health monitoring and assessment. In this paper, an urban tree health index (UTHI) is first developed to indicate the health of urban IoT trees. The index will facilitate preventive measures on urban trees. To construct the indexing model, seven (7) dynamic (time-series) features and seven (7) static features are extracted to explore the ambient effects on urban tree health. Afterward, a heterogeneous neural network (HNN) for UTHI modeling is developed to adopt the heterogeneous feature structure. In HNN, the dynamic features are analyzed in the gated recurrent unit (GRU) layer and the static features are analyzed in a hidden layer. The novel fusion layer then aggregates the outputs computed from those layers and further explores unseen correlations among all features. The experimental result verifies that the HNN-based modeling achieves high accuracy and model fitness with the error rate of less than 5%. In addition, the HNN achieves 34% to 66% improvement of accuracy in comparison with the other machine learning algorithms. The supremacy of the developed model is that all indexing features can be predefined or monitored by the IoT sensors, thus rendering an automated and economic urban tree management.

INDEX TERMS

Tree health assessment, heterogeneous neural network, modeling.

I. INTRODUCTION

The urban trees have made great positive impact to environment and citizen health. The direct benefits of the trees include cooling environment, regulating humidity, filtering urban pollutants, absorbing carbon dioxide, and improving air quality etc. Increasing the number of urban trees proliferates those benefits but risk potential and management cost will increase accordingly. In the US, the number of urban trees exceeds 3.5 billion [1]. The total compensatory value of the trees, consisting of removal cost, replacement cost, costs of settling tree damages and deaths, insurance claim, and loss of property value etc., is more than $2 trillion USD.

About 10 million trees can save $50 million USD per year from the expenditure of air conditioning [2].

The contributions made by urban trees worth $500 million USD [3]. The literatures prove that the urban trees are beneficial to human mentality and physical health, such as reducing stress level and blood pressure [4]. Besides, the urban trees provide foods and habitats to animals and other plants, thus enhancing urban biodiversity. However, tree failures may cause fatal accidents and economic losses especially in extreme weather, such as typhoon and hurricane. The risk rating of a tree is composed of three factors, namely (1) likelihood of tree failure, (2) damage factor, and (3) target rating factor. The likelihood of tree failure is the probability of tree part to fall. The damage factor measures the size of tree part likely to fall. The target rating factor measures the frequency of the target being used. The target, affected by tree failure, refers to the area occupied by either of human beings, property, or human activities. As such, the tree health assessment facilitates the arborists to estimate the likelihood of tree failure.
The International Society of Arboriculture (ISA) is a global association that certifies arborists and manifests guidance on tree health assessment [5]. Meanwhile, the researchers have proposed various simplified and fast assessment schemes to improve assessment efficiency [6]–[9]. Up to this point, most conventional tree health (and risk) inspections are conducted manually that are inefficient and cause high management cost. The annual management cost is estimated at $30 million USD [10]. Therefore, an automated tree health monitoring and assessment scheme is demanded.

The Internet-of-things (IoT) is a concept of mega integration and it proliferates the deployment of wireless sensors for various applications. Smart applications can be realized by employing artificial intelligence to analyze the data generated from the IoT network. An IoT tree is a tree equipped with various types of sensors. The sensors are connected to the IoT network and provide data for tree health analysis. Such method greatly increases the efficiency of tree health assessment and facilitates the urban tree planning.

In this paper, an Urban Tree Health Index (UTHI) is designed to efficiently evaluate the health of urban IoT trees. The UTHI is composed of five (5) levels: (Level 5) Excellent, (Level 4) Good, (Level 3) Fair, (Level 2) Poor, and (Level 1) Dying. The likelihood of tree failure increases with the drop of UTHI level. There are three (3) fundamental requirements on the extraction of indexing features. First, the features should demonstrate significant impact to the urban trees. Second, the features should be common but show different characteristics in various situations (i.e. various UTHI levels). Third, the data of the features can be predetermined or collected automatically. Total (14) indexing features, including 7 dynamic features and 7 static features, fulfill the captioned requirements and are extracted. The dynamic features consist of temperature, humidity, CO$_2$ concentration, luminous intensity, soil moisture content, soil pH level, and tilt angle that can be measured remotely through IoT network. The features can explore the ambient effect on a tree and they can be measured by low-cost sensors. The static features consist of growing characteristics, location, age, direction of light source, wind exposure, site condition, and rooting area and depth. Unlike dynamic features, the static features are predetermined, and their values are almost unchanged (e.g. tree species) or predictable (e.g. tree age). In addition, the static features influence tree health indirectly and may limit the long-term tree health. For example, the absorption of nutrients is limited if the rooting area is too small and shallow, thus increasing the probability of tree failure. The UTHI aims to measure and predict the tree health under long-term ambient effects. Thus, the instantaneous effects, such as hazardous events, have not been considered in this paper.

Tree responses to ambient changes are slow. The sequential (time-series) data of dynamic features is thus necessary to compute an accurate UTHI model. Meanwhile, the static features are composed of nominal data and they are time-independent. As such, a heterogeneous neural network (HNN) is newly developed to adopt the heterogeneous feature structure and model UTHI. The HNN incorporates recurrent neural network (RNN) and feedforward neural network with backpropagation algorithm (NNBP).

The NNBP is employed to explore the non-linear relationship between UTHI and 1-D static feature vector. NNBP can achieve similar performance with lower complexity (i.e. less number of neurons) [11] in comparison with other types of neural network. However, NNBP does not perform well for sequential input (i.e. 2-D dynamic feature matrix). RNN attributed to its internal memory is employed to solve the issue. As such, Gated Recurrent Unit (GRU) has demonstrated its superiority on sequential data processing [12], [13] compared to other types of RNN. Therefore, it will be customized into the HNN. The fusion layer in HNN will aggregate and explore the correlation between dynamic features and static features. Finally, the output layer will predict the UTHI of IoT trees. According to the experimental result, the HNN-based modeling achieves low error rate of less than 5%. Also, its root mean squared error (RMSE) and the coefficient of determination ($R^2$) are 0.217 and 0.975 that indicate good model fitness.

The contributions of this paper are:

1. A new index, namely Urban Tree Health Index (UTHI), is developed and modeled to indicate the health of urban IoT trees, thus improving the efficiency of tree health (and risk) assessment, and yet facilitating early warning and protecting public safety.

2. A heterogeneous indexing feature vector, consisting of dynamic and static features, is designed to explore the ambient effects on tree health and build UTHI classifier.

3. A heterogeneous neural network (HNN) for UTHI modeling is developed in attempt to adopt the heterogeneous feature structure and analyze the correlation among all features. The experimental result verifies that the HNN-based model achieves low error rate of 5% and high model fitness (RMSE of 0.217 and $R^2$ of 0.975).

This paper is structured as follows. The modeling algorithm of UTHI is presented in Section II. The performance evaluation and results are shown in Section III. Finally, conclusion is drawn in Section IV.

II. MODELING OF URBAN TREE HEALTH INDEX

An automated tree health assessment is demanded to improve the efficiency and it can be realized by incorporating sensor monitoring network with AI-based assessment algorithm. In this paper, an automated assessment scheme is developed to evaluate and index the health of urban trees, namely Urban Tree Health Index (UTHI). The modeling flow of the proposed scheme is shown in Fig. 1 and it can be divided into three (3) stages. At stage 1, the targeted tree health is estimated through tree health inspection to provide references for...
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FIGURE 1. The model development for Urban Tree Health Index (UTHI).

UTHI modeling. Afterward, at stage 2, the indexing features including dynamic features (DFs) and static features (SFs), which can be measured by sensors and predetermined, are extracted to construct automated AI-based tree health assessment scheme. At stage 3, an AI-based UTHI modeling is developed to recognize the patterns of tree health (from stage 1) in connection with the indexing features (from stage 2). Finally, the UTHI indexing system is realized with the developed model and it will facilitate the UTHI prediction of all urban trees.

A. STAGE 1: ESTIMATION OF URBAN TREE HEALTH

The International Society of Arboriculture (ISA) is a global endorsed association to certificate arborists for tree health assessments [5]. It is worthwhile to point out that trees can adapt their growing environments. In different cities, the standards of tree health assessments can be slightly different due to the customizations with respect to the climates, land conditions, and other environmental factors.

A generic formula representing the relationship between UTHI and the assessment criteria $C$ is formulated as follow:

$$\text{UTHI} = \frac{\sum_{i=1}^{NC} \Omega_i \times C_{N,i}}{NF - 1} \times U,$$

where $NC$ is the total number of assessment criteria. $C_{N,i}$ denotes the $i$-th normalized assessment criterion with $NF$ number of levels ($NF$ is also known as normalization factor). It means that each criterion is normalized to an integer within a specific range $[0, NF]$. Different criteria usually have different importance levels. $\Omega_i$ is a weighting factor for the $i$-th criterion, and the sum of $\Omega_i$ equals to one. The parameter $U$ represents scoring coefficient to scale the UTHI and it will determine the range of UTHI as $[0, U]$.

As previously mentioned, the assessments are usually customized to the urban characteristics. The customization can be implemented through adopting the weighting factors and criteria. This paper considers Hong Kong as the study case for performance evaluation. According to the guidelines on tree risk assessment and management provided by the Tree Management Office of Hong Kong [14], total 28 criteria were extracted to estimate the urban tree health as shown in Fig. 1. The criteria are categorized into four conditions with respect to different parts of trees, namely general condition $G$, branch condition $B$, trunk condition $T$, and root condition $R$.

The customized formulation of UTHI with respect to Hong Kong environment is (2), as shown at the bottom of this page, where the subscript $N$ denotes the normalized value with $NF$ number of levels. The numbers of criteria are represented by $NG$, $NB$, $NT$, and $NR$ in accordance with four conditions $G$, $B$, $T$, and $R$, respectively. The $\omega_G$, $\omega_B$, $\omega_T$, and $\omega_R$ are the weighting vectors indicating the importance levels of all criteria in $G$, $B$, $T$, and $R$, respectively. Note that the sum of all weighting vectors should be equal to one.

$$\text{UTHI} = \frac{\sum_{i=1}^{NG} \omega_G \times G_{N,i} + \sum_{i=1}^{NB} \omega_B \times B_{N,i} + \sum_{i=1}^{NT} \omega_T \times T_{N,i} + \sum_{i=1}^{NR} \omega_R \times R_{N,i}}{NF - 1} \times U$$
The customized UTHI is consistent to the generic formula and the importance levels of all criteria are reflected by the weighting vectors. The values of the weighting entries are estimated using analytic hierarchy process (AHP) which makes use of pairwise comparisons between every criterion pair. The professionals will evaluate and quantize the difference in the importance level of every criterion pair. For instance, the quantized difference \( \Delta_{ij} \) can be in the range of \([1, D]\) where \( D \) is the maximum degree of the importance difference. For \( \Delta_{ij} = 1 \), the \( i \)-th criterion has same importance level as the \( j \)-th criterion. For \( \Delta_{ij} = D \), the \( i \)-th criterion is more important than the \( j \)-th criterion by \( D \) degrees.

B. STAGE 2: EXTRACTION OF INDEXING FEATURES

Feature extraction is one of the most essential processes in pattern recognition. Proper feature extraction will significantly improve the recognition performance and prediction accuracy. The features should be closely related to the target objects (trees). Also, they can be commonly found in all situations and have significant changes among various situations.

To realize an automated tree health assessment, the features should be measured automatically through sensor networks. The above-mentioned assessment criteria are inspected manually and thus they are not suitable to become the features in automated assessment scheme. In brief, the features in this application should fulfill the following requirements:

1) The features have significant impact to the targets (i.e. urban trees);
2) The features are common but show different characteristics in various situations (i.e. various UTHI levels);
3) The data of the features can be predetermined or measured automatically.

In this paper, fourteen (14) indexing features are proposed and they fulfill the captioned requirements. The features are divided into two types, namely dynamic features (DF) and static features (SF). The dynamic features measure the unpredictable ambient effects on IoT trees. Their values are measured by IoT sensors. The static features measure the intrinsic tree properties and predictable ambient effects. Their values can be predetermined or calibrated. The details of the indexing features are presented as follows.

1) DYNAMIC FEATURES

The dynamic features are extracted from sequential data (time-series data) and their values are time-varying, such as diurnal variation of temperature. There are total seven (7) dynamic features including temperature (DF1), humidity (DF2), CO₂ concentration (DF3), luminous intensity (DF4), solid moisture content (DF5), soil pH level (DF6), and tilt angle of tree (DF7). It is commonly known that these features affect the tree growths as well as the tree health. Thus, they are suitable to become indexing features.

Since tree responses to the features are slow, the features are measured regularly with time interval \( \Delta_{t} \) in a period of \( T \). The period \( T \) can typically set as 52 weeks (equivalent to one year). The dynamic feature matrix \( X_{DF} \) is expressed as:

\[
X_{DF} = \begin{bmatrix}
DF_{1,1} & DF_{1,2} & \cdots & DF_{1,NDF} \\
DF_{2,1} & DF_{2,2} & \cdots & DF_{2,NDF} \\
\vdots & \vdots & \ddots & \vdots \\
DF_{T,1} & DF_{T,2} & \cdots & DF_{T,NDF}
\end{bmatrix}
\]

where NDF is the total number of dynamic features. The matrix entry \( DF_{t,i} \) is the data of \( i \)-th dynamic feature at \( t \)-th measurement and it is represented by real value, i.e. \( DF_{t,i} \in R \) for \( t = 1, 2, \ldots, T \) and \( i = 1, 2, \ldots, \text{NDF} \). The dimension of the dynamic feature matrix equals to \((T/\Delta_{t}) \times \text{NDF}\).

2) STATIC FEATURES

The static features influence the tree health indirectly while the dynamic features influence the health directly. Also, the static features may limit the tree growth and thus the long-term tree health. For instance, site condition including slope (e.g. trees on slopes), obstacles (e.g. trees under building canopies), surface attachment (e.g. stonewall trees) etc., will not directly impact the tree health. However, the tree risks (e.g. tree falling) will gradually increase while the trees are growing bigger and bigger.

The static features are predetermined, and their values are almost unchanged (e.g. tree species) or predictable (e.g. tree age). There are total seven (7) static features covering growing characteristics (SF1), location (SF2), age (SF3), direction of light source (SF4), wind exposure (SF5), site condition (SF6), and rooting area (SF7). The details of the static features are listed in TABLE 1.

Although the static features are nearly unchanged, they will influence the tree health and closely relate to the dynamic features. For example, tree species (SF1), tree age (SF2), direction of light source (SF4) and wind exposure (SF5) are the natural causes of tree leaning. The indexing system should consider all these factors when it analyzes the feature of tree tilting angle (DF7). There are hidden correlations among features and they will be analyzed and modelled through employing machine learning algorithm. The detail will be further discussed in stage 3: modeling algorithm for the UTHI.

To reduce the modelling complexity, each static feature SF\(_i\) is represented by a set of discrete levels within a range of \([1, I_{SF,i,\text{max}}]\) for \( i = 1, 2, \ldots, 7 \) and \( SF_{i}, I_{SF,i,\text{max}} \in \mathbb{N}^+ \). The trees demonstrating similar characteristics in \( i \)-th static feature will be categorized into the same SF\(_i\) level. For example, if tree A and tree B prefer similar growing environment and their structures are similar, their SF\(_i\) levels will be the same.

The static feature vector \( X_{SF} \) is expressed as:

\[
X_{SF} = \begin{bmatrix}
SF_1 & SF_2 & \cdots & SF_{\text{NSF}}
\end{bmatrix}
\]

where NSF denotes the number of static features.

It is clearly observed that dynamic features are time-series data and static features are nominal data. The dimension of \( X_{DF} \) is \((T/\Delta_{t}) \times \text{NDF}\) and the dimension of \( X_{SF} \) is \( 1 \times \text{NSF} \).
TABLE 1. The static features for UTHI modeling.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Static Feature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SF₁</td>
<td>Tree Growing Characteristics</td>
<td>The tree species will determine the optimal tree growing environment as well as the tree structures (e.g. sizes and depths of roots, crown sizes, trunk sizes etc.) at different ages. Those factors are categorized into tree growing characteristics.</td>
</tr>
<tr>
<td>SF₂</td>
<td>Tree Location</td>
<td>The tree locations can be used to determine the climate in where the trees located and evaluate the hazards due to tree failures.</td>
</tr>
<tr>
<td>SF₃</td>
<td>Tree Age</td>
<td>The tree ages are related to the tree health and the tree adaptabilities to various conditions. For instance, mature trees have higher probabilities to adapt climate changes than young trees.</td>
</tr>
<tr>
<td>SF₄</td>
<td>Direction of Light Source</td>
<td>The trees always lean toward the light source due to phototropism. The lean angles are taken into consideration.</td>
</tr>
<tr>
<td>SF₅</td>
<td>Wind Exposure</td>
<td>The wind exposure of tree will impact of tree growths (e.g. size, stiffness ...). The wind with sever strength will increase the risk for tree falling.</td>
</tr>
<tr>
<td>SF₆</td>
<td>Site Condition</td>
<td>The site condition will limit the tree growths as well as their long-term health and it comprises slope (e.g. trees on slopes), tree density, obstacles to tree growths (e.g. trees under building canopies), surface attachment (e.g. stonewall trees), structure of planting area (e.g. trees planting on concrete pavement).</td>
</tr>
<tr>
<td>SF₇</td>
<td>Rooting Area and Depth</td>
<td>The rooting area and depth influence not only tree health but also the strength of withstanding strong winds. If the rooting area is too small and shallow, the absorptions of nutrient and water will be limited, and the tree will be more likely to fallen during strong winds.</td>
</tr>
</tbody>
</table>

A new modeling algorithm for the UTHI is needed to adopt such heterogeneous feature structure.

C. STAGE 3: MODELING ALGORITHM FOR THE UTHI

In this stage, an AI-based modeling algorithm is customized and implemented to recognize the patterns of tree health (obtained at stage 1) in the connection with the indexing features (obtained at stage 2).

The UTHI consists of multiple levels (the levels are also known as classes in classification problems). A multiclass classification problem is thus considered. In addition, the indexing problem in this paper is a non-linear problem which requires an advanced algorithm to solve. Machine learning is a widely adopted method for pattern recognition, classification and prediction. Among all machine learning algorithms, artificial neural network (ANN) is an efficient and accurate supervised learning algorithm for the applications with multiple classes. The literatures demonstrated that ANN outperforms other machine learning algorithms in complex, non-linear and multiclass problems [15], [16].

A heterogeneous neural network (HNN) is designed to adopt the heterogeneous input structure and model the UTHI. The HNN incorporates recurrent neural network (RNN) and feedforward neural network with backpropagation algorithm (NNBP). The NNBP is employed to explore the non-linear relationship between UTHI and 1-D $X_{SF}$. Compared with other types of ANN, such as extreme learning machine (EML) and radial basis function (RBF), the NNBP can achieve similar performance with lower complexity (i.e. less number of neurons) [11]. However, NNBP does not perform well for sequential input (i.e. 2-D $X_{DF}$). RNN is studied and employed to resolve the issue.

RNN is a widely used candidate to solve the regression and classification problems consisting of sequential inputs (e.g. 2-D $X_{DF}$), attributed to its internal memory. Long Short-term Memory (LSTM) [17] and Gated Recurrent Unit (GRU) are two mainstream RNN architectures, which overcome the challenges of gradient vanishing and explosion problems. Multiple gates are established into the hidden units to manage (store/ reset) the information of different time sequences. GRU is an improved architecture of LSTM through simplifying the structure without degrading performance [13].

As shown in Fig. 2, the structure of HNN consists of four layers, namely (1) input layer, (2) GRU layer for $X_{DF}$ and hidden layer for $X_{SF}$, (3) fusion layer, and (4) output layer.

1) INPUT LAYER

In the input layer, the indexing features consisting of dynamic features and static features are input to the GRU layer and the hidden layer, respectively. $X_{DF}$ breaks down into multiple $1 \times NDF$ input vectors $X_{DF,t}$ of different time sequences, that is:

$$X_{DF,t} = [DF_{t,1} \quad DF_{t,2} \cdots \quad DF_{t,NDF}]$$

Afterward, $X_{DF,t}$ is input to the GRU layer sequentially from $t = 1$ to $t = T$. $X_{SF}$ is a 1-D feature vector so it can input to the hidden layer directly.

a: GATED RECURRENT UNIT (GRU) LAYER

The GRU units can explore the associations between the features of different time sequences through iterative recurrence. The output of GRU unit $h_{DF,t}$ at time $t$ considers current input $X_{DF,t}$ and previous state $h_{DF,t-1}$. The relationship between
them is represented by:

$$h_{DF,t} = G(X_{DF,t}, h_{DF,t-1})$$  \hspace{1cm} (7)

where $G$ denotes the transfer function of GRU unit. The details of the function are illustrated as follows:

$$z_t = \sigma(W_cX_{DF,t} + U_c h_{DF,t-1} + b_c)$$  \hspace{1cm} (8)

$$r_t = \sigma(W_rX_{DF,t} + U_r h_{DF,t-1} + b_r)$$  \hspace{1cm} (9)

$$c_t = \tanh(W_cX_{DF,t} + U_c(r_t \circ h_{DF,t-1}) + b_c)$$  \hspace{1cm} (10)

$$h_{DF,t} = (1 - z_t) \circ h_{DF,t-1} + (z_t \circ c_t)$$  \hspace{1cm} (11)

where $\circ$ denotes the elementwise multiplication. $z_t, r_t,$ and $c_t$ represent the reset gate, update gate and internal state, respectively. $W$ and $U$ are the weighting matrices. $b$ denotes the bias. $\sigma$ is the sigmoid activation function and tanh is the hyperbolic tangent activation function. The GRU unit will forget previous states if the reset gate is activated. The update gate determines the amount of previous states to move forward to future states.

The output of GRU layer will be fed into fusion layer and fuse with the output of hidden layer.

$b$: HIDDEN LAYER

The input-hidden structure is a feedforward structure without internal memory or recurrence, which is sufficient to process 1-D static feature vector of $X_{SF}$. The literature demonstrated that ANN with single layer of hidden layer can solve most of the complex regression and classification problems [18]. Thus, only one hidden layer is employed in this study.

In the hidden layer, each hidden unit connects to multiple inputs with a weighting vector. As previously mentioned, non-linear problem is considered in this study. The activation function in the hidden layer will yield a non-linear decision boundary to solve the problem.

Suppose there are $S$ hidden units in the hidden layer. For the $j$-th hidden unit, its output $h_{SF,j}$ is expressed as follows:

$$h_{SF,j} = f_t(\sum_{i=1}^{NSF} w_{h,ji}X_{SF,i} + b_{1,j})$$  \hspace{1cm} (12)

where $w_{h,ji}$ is the weighting of the connection from the $i$-th feature to $j$-th hidden unit. $b_{1,j}$ is the bias of the $j$-th hidden unit. $X_{SF,i}$ represent the $i$-th element in the feature vector of $X_{SF}$. $f_t$ is the activation function and it refers to sigmoid function in this case.

All outputs of hidden units are fed into the fusion layer for further processing.

2) FUSION LAYER

The outputs of GRU layer and hidden layer are integrated in the fusion layer. In most situations, the correlations among different features are difficult to be directly observed, especially the heterogeneous features as in this study. As such, feature integration (or so-called data fusion) can explore the feature correlation without loss of the unique property of each feature. The performance is usually improved using the integrated feature representation [19].

Suppose there are $F$ hidden units in the fusion layer. The formulation of the $k$-th output of the fusion layer is derived:

$$s_k = f_3(\sum_{j=1}^{S} w_{f,kj}h_{SF,j} + w_{f,kT}h_{DF,T} + b_{2,k})$$  \hspace{1cm} (13)

where $w_{f,kj}$ is the weighting of the connection from the $j$-th unit in hidden layer to the $k$-th unit in fusion layer. $w_{f,kT}$ is the weighting of the connection from the GRU unit of the final state $T$ to the $k$-th unit in fusion layer. $b_2$ is the bias in fusion layer. $f_3$ is the sigmoid activation function to produce a transformed fused feature representation.

3) OUTPUT LAYER

The output layer is the final stage of the HNN and produces the overall network output that is UTHI level. The configuration connecting the output layer and the fusion layer is a fully-connected network. The output units compute the final output using the fused feature representation in previous layer.

Since UTHI consists of multiple levels ranged from $[0, U]$, the number of output neurons is $(U + 1)$. The output unit $y_l$, for $l = [1, U + 1]$, is formulated as:

$$y_l = f_2(\sum_{k=1}^{F} w_{o,lk}s_k + b_{3,l})$$  \hspace{1cm} (14)

where $w_{o,lk}$ is the weighting of the connection from the $k$-th unit in fusion layer to the $l$-th output unit. $b_{3,l}$ is the bias of the $l$-th output unit. $f_2$ is the activation function. Softmax activation function is used to solve the multiclass problem. The probabilistic output produced by the softmax function facilitates the decision making on multiclass problems [12].

The training of the conventional neural networks requires to minimize the error between the network outputs ($y_n$) and the target outputs ($y_n$). Since HNN involves the fusion of heterogeneous features, regularization term [20] for regulating fusion process is adopted and customized into the training objective. Considering all captioned training factors, the following objective function is formulated to train HNN.

$$\min_{W_L} F = \sum_{n=1}^{N_T} ||y_n - y_n(X_{DF}, X_{SF})||^2 + \Lambda_1 \Phi(W_L) + \frac{\Lambda_2}{2} ||W_L||_{2,1} + \Lambda_3 ||W_L||_{1,1}$$  \hspace{1cm} (15)

where $N_T$ represents the total number of training data. $W_L$ is the weighting matrix of all layers. $\Lambda_1$, $\Lambda_2$, $\Lambda_3$, and $\Lambda_4$ are regularization constants.

The first term is the empirical loss function measuring the squared error between the network outputs and the target outputs. The second term is the regularization term named Euclidean norm to prevent overfitting. The third term is the $L_2,1$ norm to regularize the fusion process through exploring the feature correlation. The last term is to support the Euclidean norm on the estimation of feature correlation. The formulated optimization problem can be solved by gradient descent method.
III. PERFORMANCE EVALUATION AND RESULTS

The performance of HNN-based UTHI indexing is demonstrated and discussed in this section. Before that, the experimental setup is presented. As shown in Fig. 3, an IoT tree was equipped with multiple sensors including temperature and humidity sensor, CO₂ sensor, light sensor, soil moisture sensor, soil pH meter, tilt sensor. All sensors were connected to IoT network for remote and automated data collection of dynamic features. The prototype of single tree costed about $30. The static features were measured during sensor installation on the IoT tree. Ground-truth labels (i.e. tree health) for all features were necessary to train the UTHI model. To obtain them, the tree health of each IoT tree was inspected as introduced in the section IIA. The sample distribution of different UTHI is shown in TABLE 2.

Two error measurements are adopted to evaluate and compare machine learning algorithms on UTHI modeling. Root mean squared error (RMSE) is a commonly adopted tool to measure the errors between actual values \( y_a \) and model-predicted values \( y_p \). A good model should have low RMSE. Another evaluation metric is the coefficient of determination \( R^2 \) which indicates the fitness of the model. The fitness is said to be high if \( R^2 \) is close to 1. The calculation of RMSE and \( R^2 \) are [18]–[23]:

\[
\text{RMSE} = \sqrt{\frac{1}{N_t} \sum_{n=1}^{N_t} (y_{a,n} - y_{p,n})^2}
\]

\[
R^2 = 1 - \frac{\sum_{n=1}^{N_t} (y_{a,n} - y_{p,n})^2}{\sum_{n=1}^{N_t} (y_{a,n} - \overline{y_{a,n}})^2}
\]

where \( N_t \) is the total number of testing samples and \( \overline{y} \) denotes the mean value.

A. INDEXING PERFORMANCE OF HNN

First, the indexing performance of HNN is analyzed as shown in Fig. 4. The x-axis is the actual UTHI obtained from (2) and the y-axis is the predicted UTHI using HNN. It is observed that most predicted values align with the actual values on the line of \( f(x) = x \). The evaluation metrics are also computed. The RMSE is 0.217, and \( R^2 \) is 0.975. The metrics indicate that the HNN using the extracted indexing features can successfully model the UTHI with high fitness. The error rate of the HNN classification, which measures the rate of misclassification, is computed to give an alternative indication. It is found that the HNN achieves significant low error rate of 4.7%.

B. EFFECT OF HETEROGENEOUS STRUCTURE

The effect of heterogenous structure is studied and compared with prime ANN and RNN as shown in Fig. 5. The heterogenous indexing features consist of sequential data (dynamic features) and static features (static features). It is worthwhile to point out that ANN is not suitable to process sequential data while RNN does. Based on the results, the evaluation metrics are obtained as follows. For ANN, its RMSE and \( R^2 \) are 0.618 and 0.809, respectively. There are significant drops in both metrics compared with the HNN due to the low capability of ANN on learning sequential data. On the other hand, the effect of static features is evaluated by comparing
the performances of RNN and HNN. The RNN employs GRU layer only to learn the sequential data. This means that the static features are excluded in RNN. After training RNN, it achieves RMSE of 0.412 and $R^2$ of 0.914. The error rates of ANN and RNN are 36.8% and 17.0%, respectively. The performance of RNN is better than ANN that indicates sequential data is essential to analyze tree health. Tree responses to the environmental changes are slow, and thus sequential data is essential to analyze tree health. The comparison between the performances of RNN and HNN reveals that the static features make a significant contribution to model UTHI. There are some intrinsic properties (static features) that may influence the preferred growing environment (dynamic features). The correlation between the intrinsic features and the preferred growing environment is learned through the fusion process in HNN, thus improving the modeling accuracy.

**C. COMPARISON WITH OTHER MACHINE LEARNING ALGORITHMS**

The developed HNN is compared with other machine learning algorithms on UTHI modeling. The algorithms include support vector machine (SVM), K-nearest neighbor algorithm (K-NN), decision tree, and random forest. The computation cost in terms of training time is also introduced to compare algorithm complexity.

The comparison result is shown in Table 3. It is observed that the models trained by SVM and K-NN have poor performance (RMSE and $R^2$). This reveals that they are not suitable to learn sequential features/heterogeneous features. Decision tree and random forest achieve better performance than that of SVM and K-NN, attributed to the capability of handling numerical and categorical features. Also, decision tree has the lowest complexity in model training. Nevertheless, the proposed HNN achieves the best modeling performance (RMSE and $R^2$). It achieves the improvements of 34% to 66% on modeling performance in comparison with other algorithms.

<table>
<thead>
<tr>
<th></th>
<th>UTHI</th>
<th>RMSE</th>
<th>$R^2$</th>
<th>Training Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>0.648</td>
<td>0.782</td>
<td>8.4</td>
<td></td>
</tr>
<tr>
<td>K-NN</td>
<td>0.621</td>
<td>0.768</td>
<td>103.1</td>
<td></td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.536</td>
<td>0.825</td>
<td>4.3</td>
<td></td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.330</td>
<td>0.943</td>
<td>58.7</td>
<td></td>
</tr>
<tr>
<td>HNN (Proposed)</td>
<td>0.217</td>
<td>0.975</td>
<td>115.5</td>
<td></td>
</tr>
</tbody>
</table>

**IV. CONCLUSION**

A novel Urban Tree Health Index (UTHI) for Internet-of-things (IoT) trees has been developed to realize efficient tree health assessment. It will facilitate the urban tree planning, such as restricting activities in the region with low average UTHI and arranging tree maintenance priority. Total 14 indexing features for UTHI modeling are identified. They are composed of 7 dynamic features and 7 static features. The dynamic features are measured by deployed sensors and they reveal the ambient effect on tree health. Since tree responses to the ambient effect are slow, sequential (time-series) data are used to construct the dynamic feature matrix. The static features indicate the intrinsic properties which cannot be captured by the sensors. These features influence the tree health indirectly and may limit the tree growth and health. They are composed of nominal data and almost time-independent. To deal with the heterogeneous feature structure in the input layer, a heterogeneous neural network (HNN) for UTHI modeling has been newly developed to analyze the correlation among the features. The experimental result has verified that the HNN-based algorithm can accurately model UTHI. Its error rate is less than 5%. Furthermore, compared with other machine learning algorithms, HNN has achieved a merit of 34% to 66% improvements of accuracy. The efficient tree health assessment scheme using UTHI model can reduce annual management expenditure and provide safe and green urban environment.

**REFERENCES**


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