# Artificial Intelligence Applications in allergic rhinitis diagnosis: Focus on Ensemble Learning

Fu Dai[1], Yifei Meng [2], Shiwang Tan [3], peng Liu [4], Chuanliang Zhao [5], yue Qian[6], Jingdong Yang[2], and Shaoqing YU[7]

[1] Department of Otorhinolaryngology, Antin Hospital, Shanghai 200065, China
[2]University of Shanghai for Science and Technology
[3]Tongji University
[4]Department of Otorhinolaryngology-Head and Neck Surgery, Tongji Hospital, Tongji University School of Medicine
[5]Department of Otorhinolaryngology-Head and Neck Surgery, Tongji Hospital, Tongji University School of Medicine, Shanghai 200065, China
[6]Department of Otorhinolaryngology, Antin Hospital, Shanghai 200065, China
[7]Tongji Hospital, Tongji University, Shanghai, China

July 2, 2020

**Abstract**

Background and purpose: Artificial intelligence is an important product of the rapid development of computer technology today. This study intends to propose an intelligent diagnosis and detection method for AR based on ensemble learning. Method: This study collectedAR cases and other 7 types of diseases with similar symptoms:Rhinosinusitis, Chronic rhinitis, upper respiratory tract infection etc.) and collected clinical data such as medical history, clinical symptoms, allergen detection and imaging. Multiple models are used to train the classifier for the same batch of data, and the final ensemble classifier is obtained by using the ensemble learning algorithm. 5 common machine learning classification algorithms were selected for comparative experiments, including Naive Bayes (NB), Support Vector Machine (SVM), Logistic Regression (LR), Multilayer Perceptron (MLP), Deep Forest (GCForest), eXtreme Gradient boosting (XGBoost). In order to evaluate the prediction results of AR samples, parameters such as Precision, Sensitivity, Specificity, G-Mean, F1-Score, and AUC under the ROC curve are jointly used as prediction evaluation indicators. Results: 7 classification models are used for comparison, covering probability model, tree model, linear model, ensemble model and neural network models, and the comprehensive classification evaluation index is lower than the ensemble classification algorithms ARF-OOBEE and GCForest. Compared with other algorithms, the accuracy of G-Mean and AUC parameters is improved nearly 2%, and it has good comprehensive classification characteristics for massive large data and unbalanced samples. Conclusion: The ensemble learning ARF-OOBEE model has good generalization performance and comprehensive classification ability to be used for diagnosis of AR.

**Key Words:**

Artificial intelligence; Allergic rhinitis; Diagnosis; Deep learning; Machine learning; Ensemble learning Introduction

Allergic rhinitis (AR) is a common chronic inflammation of the upper respiratory tract. It has been considered as a type of stubborn disease that seriously affects people's daily lives. The prevalence of this disease is showing a high trend globally. About 500 million people worldwide suffer from AR, with the highest prevalence in developed regions such as Western Europe, Northern Europe and North America, generally

12-30%[1]. An AR epidemiological survey of Chinese adults showed that it rose from 11.1% in 2005 to 17.6% in 2011[2,3]. It is a type I allergic disease mediated by IgE with multiple cytokines involved. The pathogenesis of AR is related to many factors, and the specific pathogenesis is not yet clear. Various cells, proteins and cytokines produced by the patient's body may participate in or promote the occurrence and development of AR.

The typical symptoms of AR are paroxysmal sneezing, watery nasal discharge, itchy nose and stuffy nose, which may be accompanied by eye symptoms including itchy eyes, tearing, redness and burning sensation, etc. The main signs of AR are bilateral swelling of the nasal mucosa, edema of the lower turbinate, and a lot of watery discharge in the nasal cavity. The main signs of AR are bilateral nasal mucosa pale and edema, inferior turbinate edema, and a large amount of watery discharge in the nasal cavity[4]. The allergic signs of the eye are mainly hyperemia and edema, and AR patients accompany with asthma, eczema and dermatitis also have other signs of lungs and skin. In addition to symptoms and signs, the diagnosis of this disease also depends on the detection of allergens, including in vivo tests (skin prick test SPT) and in vitro tests (blood tIgE and sIgE tests), and nasal provocation test[5]. In addition, nasal secretion smears and sIgE in nasal lavage fluid are also helpful for clinical diagnosis[6]. Endoscopy or computed tomography (CT) can observe changes in signs such as hypertrophy of the turbinate, swelling of the mucosa, and help to diagnosis of diseases such as sinusitis and nasal polyps[7].

The diagnosis of AR is mainly based on symptoms and signs, as well as laboratory tests, but due to the limitations of outpatient conditions in China, some tests are not routinely operated, such as nasal provocation test, nasal secretion smear, etc[8]. Although the nasal provocation test is the gold standard for the diagnosis of AR, it has risks and is not clinically used as a routine method. Based on medical history,it can be divided into intermittent AR: symptom onset <4 d/week, or <4 consecutive weeks and persistent AR: symptom onset [?] 4 d/week, and [?] 4 consecutive weeks. And according to the severity of the symptoms, it also can be divided into mild AR: mild symptoms, no significant impact on quality of life (including sleep, daily life, work and study) and Moderate-severe AR: severe symptoms, affecting quality of lifesignificantly (including sleep , daily life, work and study).

Although there are more feasible diagnostic criteria, in clinical practice, experienced doctors are still required to make an accurate diagnosis based on medical history, examination, living habits, etc. However, due to individual differences and limitations of inspection methods, inconsistencies in diagnosis may still occur. Artificial intelligence(AI) is a cutting-edge and cross-disciplinary disciplinethat develops theories, methods, technologies, and application systems for simulating,extending, and expanding human intelligence[9].AI has been widely used in various industries in recent years, and has developed powerful mathematical models algorithm such as decision trees, naive Bayes and artificial neural networks (ANN), which are used in intelligent control, pattern recognition, prediction and other fields. In recent years, ensemble learning can organically combine multiple prediction results obtained by multiple single learning models to obtain more accurate, stable and strong final results. And ensemble learning models such as Boosting, Bagging and Random Forest(RF) have been proposed one after another and applied to various types of data sets. This study hopes to explore the application of AI ensemble learning in AR clinical diagnosis through the deep learning of ensemble learning models in big data, data analysis of more than 2,000 clinical cases in outpatient service in combination with the typical characteristics of Chinese AR.

## Materials and Method

1.Sample source

clinical samples of nasal inflammation came from Tongji Hospital and Shanghai Anting Hospital, and the data collection time was 2019.4.1-2020.3.31. A total of 2231 case data were collected. The collected cases were patients with a preliminary diagnosis of suspected AR. Among them, 1335 were male (59.84%) and the average age was (35.39±19.71) years; 896 were female (40.16%) and the average age was (37.69±17.94) years old. All patients' Clinical history were obtained, including time, name, age, gender, course of disease, four symptoms: sneezing, runny nose, itchy nose, stuffy nose, two eye symptoms. The physical signs include nasal polyps and nasal secretions. Blood tests include blood routine examination, total IgE, allergen SIgE, and CT imaging tests.

This study mainly collected cases of AR and included 6 types of diseases with similar symptoms: Rhinosinusitis (RS), Chronic rhinitis(RS), upper respiratory tract infection (URI), nasal septum deviation (NSD), adenoid hypertrophy (AH) and others (OTH contains nasal tumors, etc.) and collected clinical data such as medical history, clinical symptoms, allergen detection and imaging.

The diagnosis of AR combined with medical history and clinical symptoms can be divided into four types: mild intermittent, mild persistent, moderate - severe intermittent and moderate-severe persistent. The clinical symptom score was calculated using the total nasal and ocular symptom scores (TNSS and TOSS), which were scored from four aspects: stuffy nose, runny nose, itchy nose, and sneezing.Finally, it is divided into four gradesas 0: no symptoms; 1 : mild; 2 : moderate; 3 : severe[10].

2.Experimental setup and algorithm structure design

The data records a total of 66 features including 16 symptoms and signs including eye symptoms, nasal cavity examination, and runny nose. The presence or absence of symptoms and signs are represented by 1 or 0respectively. The classification method based on association rules used in the framework is compared with other classification methods, the former is the decision tree induction method (C4.5) and the latter is the probability classification method [11].

The classification of AR symptoms is a special multi-marker learning problem, that is, a patient may be combined with other diseases at the same time. And at the same time, some labels are mutex. For example, a patient without AR should not be diagnosed with intermittent mild classification, or a patient cannot have both intermittent and persistent AR. To solve such multi-label classification problems, problem conversion method and algorithm adaptation method are usually used.

Both transformation ideas were used in this study. Convert traditional multi-label classification into multiple binary classification problems with equal number of labels, and then use various basic machine learning algorithms to train each model to build an ensemble classification model based on multi-label classification,as shown in Figure 1. Table 1 shows the different classification methods used for various rhinitis samples and types in the comprehensive classification model.

One-Hot-Encoding is used in the analysis to encode all cases. One-hot encoding is also known as one-bit effective encoding.This method is to encode N states with N-bit 0-1 features. Each state has its own 0-1 feature bit, and at any time, only one valid. One-Hot coding can handle non-continuous numerical features, and to some extent, it also expands the features. For example, case A has clinical symptoms such as ophthalmia, turbinate hypertrophy, and clear secretions. The value of case A under these symptoms is 1, and there is no tearing, pale mucosa, or mucosal congestion. The value under these symptoms is 0. Finally, the doctor diagnosed the patient as AR and nasal septum deviation,so these corresponding values are 1, and the values of other symptoms that have not appeared are 0. The specific data form of the case is shown in Table 2.All case data were processed as a symptom-diagnosis input vector for the symptom classification model

3.Unbalanced data processing

For multi-category classification, class imbalance methods include SMOTE, ADASYN, All-KNN and other methods[12]. For the multi-label classification of rhinitis, the included patients with AR accounted for 95.1% of the total patients, and a few patients with similar rhinitis symptoms had a label lower than 10% of the total sample number. This makes it difficult to achieve a balanced distribution of all categories of data. If oversampling SMOTE is applied to a small number of labels, the number of AR labels will be increased, the imbalance of the overall rhinitis symptoms data will be exacerbated, and the overall classification accuracy will be reduced[13].Analysis of the actual clinical data collected shows that if the training set and the test set are divided into minority labels, the minority samples in the test set will be reduced,which will lead to the increase of the influence of the single classification result on the comprehensive classification and affect the balance ofprediction markers and sample size. To this end, ADASYN algorithm is adopted in this study to deal with unbalanced rhinitis sample datato ensure a balanced strategy for AR and its labels,effectively improve the classification accuracy of most similar rhinitis diseases AR and its labels,and also increasing the classification accuracy of a few otherunbalanced rhinitis cases[14]. The unbalanced split of rhinitis sample data is shown in Figure 2.

4.Ensemble analysis of clinical data

To evaluate the prediction results of AR samples, select the confusion matrix comprehensive indicators: true positive (TP), false negative (FN), false positive (FP) and true negative(TN), and use precision, sensitivity, specificity, G-Mean=sqrt(Sensitivity×Specificity), F1-Score, area under ROC curve AUC and other parameters together as predictive evaluation indicators.

This study proposed a heterogeneous ensemble rhinitis classifier model (Adaptive Random Forest-Out Of Bag-Easy Ensemble, ARF-OOBEE), which can identify a variety of disease, such as sinusitis (RS) (binary variable), The severity or persistence (ordered variable) of AR (AR), etc. This model effectively avoids the interference between multi-label type classification and multi-class symptom classification by converting heterogeneous multi-output classification problems into multi-label classification problems and 2 multi-class classification problems, and two or more indexing or typing labels for the same patient at the same time. Multiple models are used to train the classifier for the same batch of data, and the final ensemble classifier is obtained by using the ensemble learning algorithm. At the same time, 6 common machine learning classification algorithms were selected for comparative experiments, including Naive Bayes (NB)[15], Support Vector Machine (SVM)[16,17], Logistic Regression (LR)[18], Multilayer Perceptron (MLP)[19], Deep Forest (GCForest)[20], eXtreme Gradient boosting (XGBoost)[21].

**Results**

**1. Clinical sample data analysis**

From the included data distribution, it can be found that there is a high incidence area of pediatric patients before the age of 10 years, and another high incidence area of rhinitis symptoms between 30 and 40 years old (Figure 3). There was no statistical difference between male and female morbidity.

According to statistics in this study, the highest diseases is AR accounted for 65.77% (1818 cases), the second highest is RS accounted for 8.90% (246 cases), the rest are: 137, 134, 130, 106, 100 and 93 cases, accounting for less than 5%. Meanwhile, the statistics of the patients' cumulative illnesses revealed that the patients had at most 3 diseases at the same time, which accounted for 1.16% (26 cases); patients with two diseases accounted for 21.56% (481 cases) and with one disease accounted for 77.27% (1724 cases).

**2. Comprehensive evaluation index**

This paper uses a random 10×2K-Folding cross-validation method to classify the samples based on the ARF-OOBEE ensemble model. Among them, after testing, the number of ensemble learning base classifiers is 70, the depth is 12, and it is compared with the prediction results of 5 common machine learning algorithms. According to the prediction index analysis in Table 3, compared with the other five algorithms, the ARF-OOBEE algorithm has improved the accuracy of G-Mean and AUC parameters by nearly 2%. It can be seen that for the AR samples with clinical imbalance characteristics, the ARF-OOBEE model has good generalization performance and comprehensive classification ability.

Precision, sensitivity, specificity, G-Mean= sqrt (Sensitivity×Specificity), F1-Score, area under ROC curve AUC and other parameters together were used as predictive evaluation indicators[22]. In Table 3 and Figure 4, 7 classification models are selected for comparison, covering probability model, tree model, linear model, ensemble model and neural network model.It comprehensively reflects the performance of the research objects in different classification models and the ensemble model has the best and most stable effect, in this paper. The comprehensive classification evaluation index is lower than the ensemble classification algorithms ARF-OOBEE and GCForest. The GCForest algorithm is composed of two RF and two extreme random tree(ERT) in parallel structure, and its multiple comprehensive evaluation indicators are better than the single structure

RF algorithm, but the classification calculation is relatively large. The structure of the ARF-OOBEE model has adaptive characteristics, which can dynamically change the number of ensemble learning base classifiers, and train the component classifier model parameters separately. It has good comprehensive classification characteristics for massive large data and unbalanced samples.

Table 4 gives the independent classification evaluation indicators of the 8 types of rhinitis symptoms data for the original sample. Data analysis shows that the prediction accuracy of AR, RS, CS, SD, URI, AH, NAR and OTH for the binary classification of rhinitis is higher, while the classification of degree and types in multi-class rhinitis is lower. The reason is that the classification of the four binary classification rhinitis is based on data rebalancing and is determined by the dynamically ensemble RF weighted voting algorithm in the ARF model. Output prediction of AR classification were estimated using an ERTensemble algorithm with multi-category classification. ARF-OOBEE ensemble model converts the compound label classification problem into a four-label classification problem as and two multi-class classification problems.Multi-label classification were used in classification of AR, RS, URI, OTH, and multi-category classification were used in classification of AR'sdegree and type respectively,and it can avoid two or more AR classification labels in the same patient at the same time

The evaluation method in this paper uses a calculation method based on sample weights. Sensitivity represents the model's ability to identify patients with real illnesses, while specificity represents the model's misdiagnosis rate, and the Hamming loss is a common way of evaluating multiple classifications. The data in the table uses weighted scores. Compared with evaluating the performance of the model itself, it more reflects its performance in actual use. Avoid the rare cases of diagnosis in reality that reduce the overall evaluation of the model. For the few cases of missed diagnosis in the auxiliary diagnosis model designed in this paper, it can be ruled out by the doctor's secondary review and other methods.

Discussion

In recent years, the prevalence of AR has increased significantly, and its diagnosis is more based on symptom evaluation and allergen detection, but due to the lack of effective and reliable diagnostic tests, the diagnosis requires experts to verify the final results based on experience[23,24]. In order to help junior physicians and clinicians diagnose allergic diseases, this work uses AI methods to extract new information from previous data for training[25,26]. Through the dynamic verification of the rule base and rule inference method, make the clinical diagnosis support system more adaptable. By introducing meta-heuristic data preprocessing technology and ensemble classification method, the systemefficiency can be further improved. Therefore, junior clinicians can strengthen clinical decision-making by more accurately diagnosing allergic diseases, can diagnose and treat AR earlier, can control the appearance of patients' symptoms to the greatest extent, and thus improve the quality of life of patients with AR.

The diagnosis of AR is mainly based on the symptoms and the detection of allergens[27]. However, due to the complex and variable nature of nasal inflammation, it is often combined with other diseases, such as rhinosinusitis and nasal tumors. Imaging examination helps to diagnose other diseases. Turbinate hypertrophy is also a characteristic change of AR. Our selected cases have also been found to have rhinosinusitis and nasal polyps. Therefore, the use of CT imaging can better assist the diagnosis of AR.

AI technology, without human intervention, can learn tasks from a series of training examples. Moreover, they aim to produce output that is simple enough to be easily understood by humans. The difference is that the characteristics of classical statistical methods are usually a clear probability model, and it is assumed that in most cases, they require expert intervention in variable selection and transformation of the problem and overall structure. The general method of data analysis usually includes four stages, namely (a) collecting and coding clinical data in an electronic form suitable for further processing; (b) Useing feature extraction and dimensionality reduction techniques (principal component analysis) for data processing to select the most predictive parameters; (c) Schema-model selection AI model; (d) Extract knowledge by evaluating accuracy, sensitivity and specificity[28]. At present, the most common calculation models include: artificial neural network (ANN), SVM, Bayesian network (BN) and fuzzy logic (FL),etc.

In recent years, ensemble learning can organically combine multiple prediction results obtained by multiple single learning models to obtain more accurate, stable and strong final results. For exampleensemble learning models such as Boosting, Bagging and RF have been proposed one after another and applied to various types of data sets[29,30]. In this study, through the deep learning of the ensemble learning model, six common machine learning classification algorithms have been selected for comparative experiments, including RF, multi-label naive Bayes (NB), and multi-label SVM (SVM), multi-label logistic regression (LR), GCForest. The single-classifier RF algorithm is a base classification evaluation standard, and also constitutes the base classifier component of other algorithms, with good classification specificity, but the comprehensive classification evaluation index is lower than the ensemble classification algorithms ARF-OOBEE, GCForest. The GCForest algorithm is composed of two RF and two ERT in parallel structure, and its multiple comprehensive evaluation indicators are better than the single structure RF algorithm, but the classification calculation is relatively large[31].

There are two types of output for AR diseases, degree and types, which belongs to the multi-class classification problem. This article uses the OOB (out-of-bag) EE ensemble classification algorithm and uses all samples as training data. And the Extra-Tree (ET) model is used as the base classifier to balance all training data to realize the prediction of unbalanced small samples. OOBEE extracts the data equal to the minority class from the majority class, and combines the reused minority class data to build a multi-group base classifier, and obtains the ensemble classifier through the weighted voting method to reduce the impact of sample data imbalance on classification. The structure of the ARF-OOBEE model has adaptive characteristics. It can dynamically change the number of ensemble RF and ERTbaseclassifiers, and train the component classifier model parameters separately. It has good comprehensive classification characteristics for massive large data and unbalanced samples. The results show that compared with the other five algorithms, the ARF-OOBEE algorithm has improved the accuracy of G-Mean and AUC parameters by nearly 2%. It can be seen that for the AR samples with clinical imbalance characteristics, the ARF-OOBEE model has good generalization performance and comprehensive classification ability.

There are some deficiencies in this study. First of all, the diagnosis of AR is mainly based on the symptom score and allergen detection, but some patients still have obvious symptoms while the test is negative, and need to be identified by such as nasal provocation test. However, this test cannot be widely used in the outpatient diagnosis and treatment, therefore, there will be individual cases of diagnostic errors. The artificial intelligence system is designed to help diagnosis, but it cannot completely replace the rhinologist. This study is a dual-center study conducted at Tongji Hospital of Tongji University and Anting Branch Hospital. There may be a selection bias. In the future, a multi-center study should be conducted to improve the database required for training artificial intelligence systems and improve their diagnostic capabilities. Finally, through the self-learning of the system, it can help junior doctors complete the diagnosis of AR and improve their diagnosis ability.

Ethical disclosures Confidentiality of data

The authors declare that no patient data appears in this article. Right to privacy and informed consent. The authors declare that no patient data appears in this article. Protection of human subjects and animals in research. The authors declare that no experiments were performed on humans or animals for this investigation.

Funding

This work was supported by the National Science Foundationof China (grant no. 8187040043,81973749), Western Medicine GuideProject of Shanghai City (grant no. 17411970500), ShenkangMedical Development Center Clinical Science and Technology Innovation Project of Shanghai City (grant no. SHDC12019X07), Health Commission Advanced Technology Promotion Project of Shanghai City (grant no. 2019SY071).

Conflicts of interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of this manuscript.

## References

[1]Yorgancioğlu A, Kalayci O, Kalyoncu AF, Khaltaev N, Bousquet J. Allerjikrinitveastimüzerineetkisigüncelleme (ARIA 2008). TuberkToraks. 2008;56(2):224-231.

[2]Zhang Y, Zhang L. Prevalence of allergic rhinitis in china. Allergy Asthma Immunol Res. 2014;6(2):105-113.

[3]Zheng M, Wang X, Bo M, Wang K, Zhao Y, He F, Cao F, Zhang L, Bachert C. Prevalence of allergic rhinitis among adults in urban and rural areas of china: a population-based cross-sectional survey. Allergy Asthma Immunol Res. 2015;7(2):148-157.

[4]Skoner DP. Allergic rhinitis: definition, epidemiology, pathophysiology, detection, and diagnosis. J Allergy Clin Immunol. 2001;108(1 Suppl):S2-S8.

[5]Dordal MT, Lluch-Bernal M, Sánchez MC, Rondón C, Navarro A, Montoro J, Matheu V, Ibáñez MD, Fernández-Parra B, Dávila I, Conde J, Antón E, Colás C, Valero A. Allergen-specific nasal provocation testing: review by the rhinoconjunctivitis committee of the Spanish Society of Allergy and Clinical Immunology. J InvestigAllergol Clin Immunol. 2011;21(1):1-12.

[6]Chinoy B, Yee E, Bahna SL. Skin testing versus radioallergosorbent testing for indoor allergens. Clin Mol Allergy. 2005;3(1):4. Published 2005 Apr 15.

[7]Lloyd GA, Lund VJ, Scadding GK. CT of the paranasal sinuses and functional endoscopic surgery: a critical analysis of 100 symptomatic patients. J Laryngol Otol. 1991;105(3):181-185.

[8]Cheng L, Chen J, Fu Q, He S, Li H, Liu Z, Tan G, Tao Z, Wang D, Wen W, Xu R, Xu Y, Yang Q, Zhang C, Zhang G, Zhang R, Zhang Y, Zhou B, Zhu D, Chen L, Cui X, Deng Y, Guo Z, Huang Z, Huang Z, Li H, Li J, Li W, Li Y, Xi L, Lou H, Lu M, Ouyang Y, Shi W, Tao X, Tian H, Wang C, Wang M, Wang N, Wang X, Xie H, Yu S, Zhao R, Zheng M, Zhou H, Zhu L, Zhang L. Chinese Society of Allergy Guidelines for Diagnosis and Treatment of Allergic Rhinitis. Allergy Asthma Immunol Res. 2018;10(4):300-353.

[9]Schwalbe N, Wahl B. Artificial intelligence and the future of global health. Lancet. 2020;395(10236):1579-1586.

[10]Kaliner MA, Berger WE, Ratner PH, Siegel CJ. The efficacy of intranasal antihistamines in the treatment of allergic rhinitis. Ann Allergy Asthma Immunol. 2011;106(2 Suppl):S6-S11.

[11]Yan J, Zhang Z, Lin K, Yang F, Luo X. A hybrid scheme-based one-vs-all decision trees for multi-class classification tasks. Knowledge-Based Systems. 2020;198:105922.

[12]Chawla NV, Bowyer KW, Hall LO, Kegelmeyer WP. SMOTE: synthetic minority over-sampling technique. Journal of Artificial Intelligence Research. 2002;16(1):321-357.

[13]Zhao J, Jin J, Chen S, Zhang R, Yu B, Liu Q. A weighted hybrid ensemble method for classifying imbalanced data. Knowledge-Based Systems. 2020;203:106087.

[14]Zhang L, Shah SK, Kakadiaris IA. Hierarchical Multi-label Classification using Fully Associative Ensemble Learning. Pattern Recognition. 2017;70:89-103.

[15]Zhang H, Liu CT, Mao J, Shen C, Xie RL, Mu B. Development of novel in silico prediction model for drug-induced ototoxicity by using naïve Bayes classifier approach. Toxicol In Vitro. 2020;65:104812.

[16]Kumar S, Ong SH, Ranganath S, Ong TC, Chew FT. Classification of airspora using support vector machines (SVM). Journal of Allergy and Clinical Immunology. 2003;111(2):S91.

[17]Gao X, Hou J. An improved SVM integrated GS-PCA fault diagnosis approach of Tennessee Eastman process. Neurocomputing. 2016;174:906-911.

[18]Mondal P, Dey D, Chandra Saha N, Moitra S, Saha GK, Bhattacharya S, Podder S. Investigation of house dust mite induced allergy using logistic regression in West Bengal, India. World Allergy Organ J. 2019;12(12):100088. Published 2019 Nov 27.

[19]Heidari M, Shamsi H. Analog programmable neuron and case study on VLSI implementation of Multi-Layer Perceptron (MLP). Microelectronics Journal. 2019;84:36-47.

[20]Zhu G, Hu Q, Gu R, Yuan C, Huang Y. ForestLayer: Efficient training of deep forests on distributed task-parallel platforms. Journal of Parallel and Distributed Computing. 2019;132:113-126.

[21]Wang C, Deng C, Wang S. Imbalance-XGBoost: leveraging weighted and focal losses for binarylabel-imbalanced classification with XGBoost. Pattern Recognition Letters. 2020;136:190-197.

[22]Izquierdo-Verdiguier E, Zurita-Milla R. An evaluation of Guided Regularized Random Forest for classification and regression tasks in remote sensing. International Journal of Applied Earth Observation and Geoinformation. 2020;88:102051.

[23]Greiner AN, Hellings PW, Rotiroti G, Scadding GK. Allergic rhinitis. Lancet. 2011;378(9809):2112-2122.

[24]Wang X, Du K, She W, Ouyang Y, Sima Y, Liu C, Zhang L. Recent advances in the diagnosis of allergic rhinitis. Expert Rev Clin Immunol. 2018;14(11):957-964.

[25]Ullah R, Khan S, Ali H, Chaudhary II, Bilal M, Ahmad I. A comparative study of machine learning classifiers for risk prediction of asthma disease. PhotodiagnosisPhotodynTher. 2019;28:292-296.

[26]Segura-Bedmar I, Colón-Ruíz C, Tejedor-Alonso MÁ, Moro-Moro M. Predicting of anaphylaxis in big data EMR by exploring machine learning approaches. J Biomed Inform. 2018;87:50-59.

[27]Wide L, Bennich H, Johansson SG. Diagnosis of allergy by an in-vitro test for allergen antibodies. Lancet. 1967;2(7526):1105-1107.

[28]Waring J, Lindvall C, Umeton R. Automated machine learning: Review of the state-of-the-art and opportunities for healthcare. ArtifIntell Med. 2020;104:101822.

[29]Kalaiselvi B, Thangamani M. An efficient Pearson correlation based improved random forest classification for protein structure prediction techniques. Measurement. 2020;162:107885.

[30]Kadkhodaei HR, Moghadam AME, Dehghan M. HBoost: A heterogeneous ensemble classifier based on the Boosting method and entropy measurement. Expert Systems with Applications. 2020;157:113482.

[31]Bhardwaj R, Hooda N. Prediction of Pathological Complete Response after Neoadjuvant Chemotherapy for breast cancer using ensemble machine learning. Informatics in Medicine Unlocked. 2019;16:100219.

Table 1 classification labels of diseases

| Rhinitis symbol | Rhinitis name | Classification criteria |
|---|---|---|
| AR | Allergic rhinitis | binary classification |
| RS | Rhinosinusitis | binary classification |
| NSD | nasal septum deviation | binary classification |
| CR | Chronic rhinitis | binary classification |
| URI | upper respiratory tract infection | binary classification |
| AH | adenoid hypertrophy | binary classification |
| NAR | Non-allergic rhinitis | binary classification |
| OTH | others | binary classification |
| Type | types classification of AR | Multi-classification |

Table 2 One-Hot encoding

| **Form of Original Data** | **Form of Original Data** | **Form of Original Data** | **Form of Original Data** | **Form of O** |
|---|---|---|---|---|
| *(*Property)* | *(*Property)* | *(*Property)* | *(*Property)* | *(*Property* |
| *Property1* | *Property2* | *Property3* | ... | *Propertyn* |
| 1 | 0 | 0 | ... | 1 |
| 0 | 1 | 0 | ... | 1 |
| ... | ... | ... | ... | ... |
| 1 | 0 | 1 | ... | 0 |

Table3.Comprehensive evaluation indicators of various machine learning algorithms

| Methods | F1-Score | Sensitivity | Precision | Specificity | Hamming Loss | Accuracy | G-M |
|---|---|---|---|---|---|---|---|
| ARF-OOBEE | 0.9022±0.0098 | 0.8949±0.0118 | 0.9151±0.0165 | 0.9805±0.0338 | 0.0296±0.0055 | 0.9704±0.0168 | 0.93 |
| GcForest | 0.9140±0.0145 | 0.8980±0.0144 | 0.9420±0.0169 | 0.9810±0.0392 | 0.0252±0.0078 | 0.9748±0.0210 | 0.93 |
| LR | 0.8052±0.0136 | 0.7905±0.0110 | 0.8622±0.0160 | 0.9581±0.0300 | 0.0520±0.0079 | 0.9480±0.0196 | 0.87 |
| NaiveBayes | 0.7587±0.0148 | 0.8085±0.0106 | 0.7404±0.0130 | 0.9113±0.0380 | 0.0962±0.038 | 0.9038±0.0213 | 0.85 |
| MLP | 0.7673±0.0152 | 0.7532±0.0126 | 0.8327±0.0165 | 0.9409±0.0099 | 0.0745±0.0380 | 0.9255±0.0226 | 0.84 |
| SVM | 0.7411±0.0133 | 0.7949±0.0119 | 0.7137±0.0135 | 0.8941±0.0333 | 0.1090±0.0083 | 0.8910±0.0212 | 0.84 |
| XGBoost | 0.8804±0.0116 | 0.8552±0.0114 | 0.9435±0.0176 | 0.9725±0.0353 | 0.0335±0.0079 | 0.9665±0.0185 | 0.91 |

Table 4 Evaluation index of ARF-OOBEE in multiple label classification

| Classification | F1-Score | Sensitivity | Precision | Specificity | Hamming Loss | Accuracy | G-M |
|---|---|---|---|---|---|---|---|
| AR | 0.9607±0.0138 | 0.9472±0.0115 | 0.9757±0.0171 | 0.9884±0.0225 | 0.0239±0.0103 | 0.9761±0.0363 | 0.96 |
| RS | 0.9808±0.0132 | 0.9733±0.0122 | 0.9886±0.0157 | 0.9984±0.0165 | 0.0060±0.0096 | 0.9940±0.0321 | 0.98 |
| NSD | 0.8687±0.0122 | 0.8687±0.0133 | 0.8687±0.0202 | 0.9875±0.0237 | 0.0243±0.0088 | 0.9724±0.0336 | 0.92 |
| CR | 0.9085±0.0136 | 0.9439±0.0134 | 0.8791±0.0241 | 0.9809±0.0245 | 0.0239±0.0087 | 0.9761±0.0362 | 0.96 |
| URI | 0.9142±0.0123 | 0.9142±0.0124 | 0.9142±0.0173 | 0.9905±0.0188 | 0.0179±0.0083 | 0.9821±0.0312 | 0.95 |
| AH | 0.9706±0.0131 | 0.9706±0.0128 | 0.9706±0.0219 | 0.9968±0.0186 | 0.0060±0.0079 | 0.9940±0.0297 | 0.98 |
| NAR | 0.7784±0.0151 | 0.7258±0.0116 | 0.8709±0.0182 | 0.9921±0.0193 | 0.0373±0.0081 | 0.9627±0.0312 | 0.84 |
| OTH | 0.7974±0.0142 | 0.7746±0.0134 | 0.8249±0.0193 | 0.9891±0.0173 | 0.0269±0.0099 | 0.9731±0.0362 | 0.87 |
| Degree of AR | 0.9270±0.0097 | 0.9234±0.0098 | 0.9311±0.0211 | 0.9466±0.0182 | 0.0597±0.0096 | 0.9403±0.0336 | 0.93 |
| Types of AR | 0.9161±0.0134 | 0.9075±0.0108 | 0.9274±0.0228 | 0.9349±0.0207 | 0.0706±0.0074 | 0.9294±0.0321 | 0.92 |

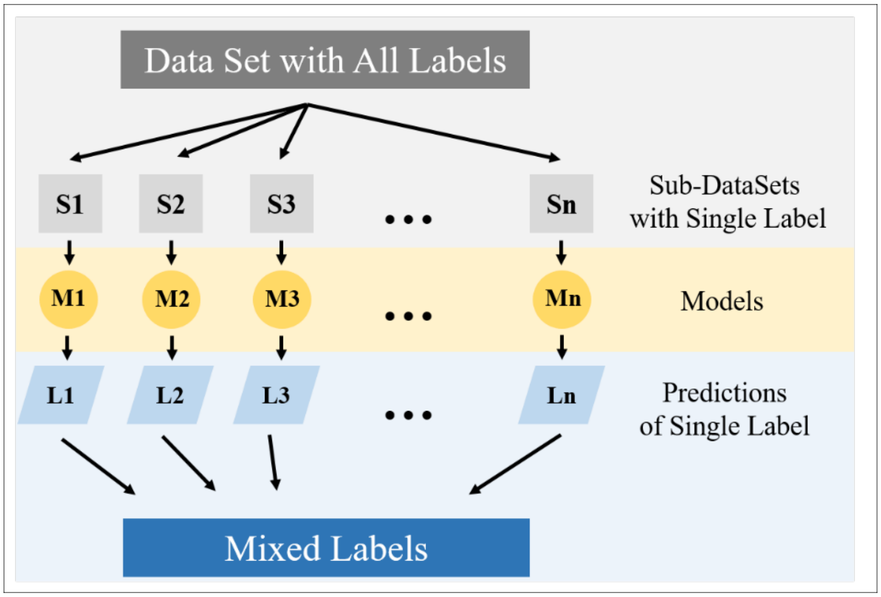
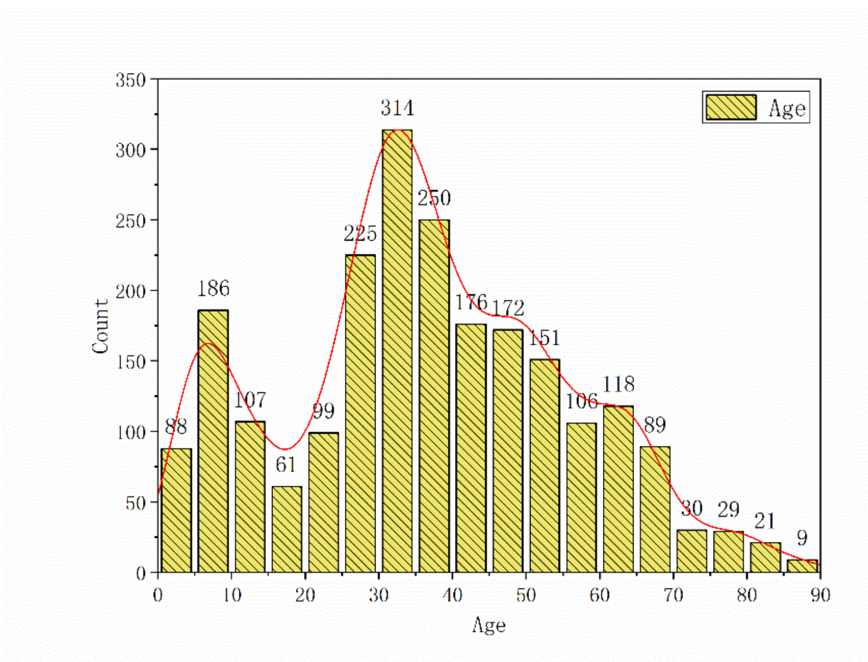
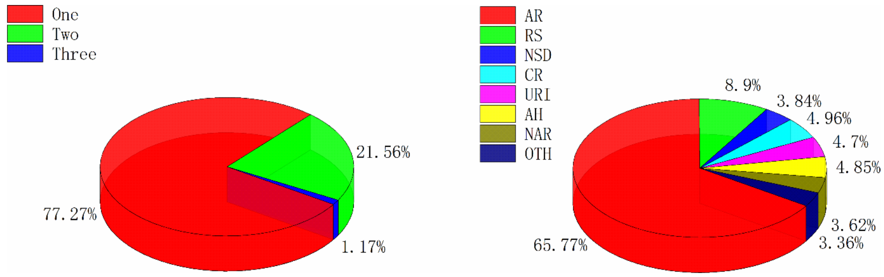



Figure 1 Multi-label classification transformation Figure 2.Rhinitis sample set split and equalization



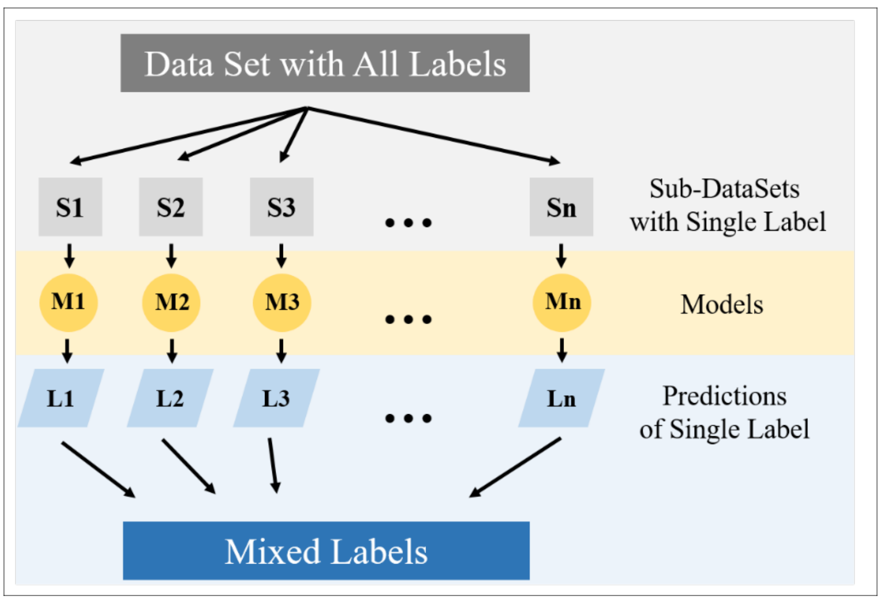

A




B

Figure 3 Age(A) and disease types(B) distribution in the samples

From the included data distribution, it can be found that there is a high incidence area of pediatric patients before the age of 10 years, and another high incidence area of rhinitis symptoms between 30 and 40 years old (A). According to statistics, among the 7 types of diseases studied in this paper, the highest is AR accounted for 65.77% (1818 cases), the second highest is RS accounted for 8.90% (246 cases), the rest are: 137, 134, 130, 106, 100 and 93 cases, accounting for less than 5%. Meanwhile, the statistics of the patients' cumulative illnesses revealed that the patients had at most 3 diseases at the same time, which accounted for 1.16% (26 cases); patients with two diseases accounted for 21.56% (481 cases) and with one disease accounted for 77.27% (1724 cases).(B)



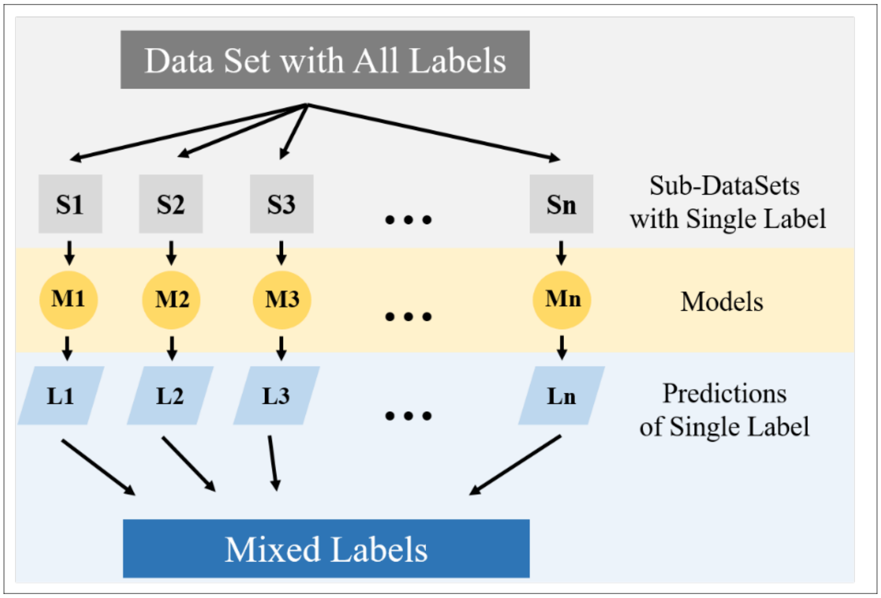



Figure 4 ROC curve for ensemble analysis

Precision, sensitivity, specificity, G-Mean= sqrt (Sensitivity×Specificity), F1-Score, area under ROC curve AUC and other parameters together were used as predictive evaluation indicators. ARF-OOBEE and 6 machine learning algorithms for comparative experiments, including Naive Bayes (NB), Support Vector Machine (SVM), Logistic Regression (LR), Multilayer Perceptron (MLP), Deep Forest (GCForest), eXtreme Gradient boosting (XGBoost).