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RESEARCH ARTICLE

The CGAS Deep Learning Algorithm for P-Wave Arrival Time Picking of Mining Microseismic Events

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ABSTRACT In light of the inadequacies of traditional P-wave arrival picking algorithms using long and short windows, which exhibit poor anti-noise ability and do not meet the requirements for efficient and accurate P-wave arrival picking, this study proposes a CGAS deep learning algorithm for P-wave arrival picking in mine micro-seismic events. The algorithm constructs the depth characteristics of microseismic waveform through deep learning training and converts the problem of picking up the microseismic waveform into a classification problem by employing data set segmentation and classification. This allows the algorithm to pick up the characteristic information of microseismic waveform and improve the accuracy of P-wave picking. The algorithm was applied to pick up the three-component micro-seismic waveforms obtained from the microseismic monitoring system in a mining area in Liaoning from 2019 to 2020. Through ablation experiments, it was found that adding each structure to the pickup model improved the relevant indexes to some extent. When all network structures were used, the accuracy of the P-wave pick-up model reached 98.61%, ensuring the accuracy of P-wave pickup upon arrival and demonstrating the effectiveness of each layer structure in the classification of P-wave arrival. Compared to other P-wave arrival picking algorithms such as STA/LTA, U-Net++, Dpick, PhaseNet and EQTransformer, the algorithm proposed in this paper exhibited high precision in P-wave arrival time picking, providing a new research idea and technical means for efficiently determining the P-wave arrival of events.

INDEX TERMS CGAS model, multi-time window, mine microseismic, P-wave arrival time picking, self-attention mechanism.

I. INTRODUCTION

The exploitation of mineral resources is currently undergoing rapid development, and as a result, environmental safety in deep mining areas has become a pressing concern [1]. The complex geological structure of underground mines and the potential for micro-seismic events to occur during the mining process pose safety hazards that cannot be overlooked.

Therefore, accurate pickup of micro-seismic signal P-wave arrivals are of great importance in event location, event identification and source mechanism analysis in order to prevent safety hazards [2]. P-wave arrival time picking is one of the basic components of micro-seismic data analysis, and improving the accuracy of P-wave arrival time picking is a core component of disaster prevention efforts [3], [4]. In the past few decades, the P-wave arrival time picking algorithms have been widely based on time series analysis or rigorous mathematical calculations, such as the STA/LTA algorithm [5], the multi-window algorithm [6], the algorithm of seismic phase monitoring based on the concept of entropy [7], the Seismic phase pickup algorithms developed based on higher-order statistics [8], [9]. STA/LTA is the ratio between

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the amplitude, of the signal on a short time window of length STA and on a long time window of length LTA. At a given point STA/LTA is computed for the time windows preceding the point [5]. The multi-window algorithm method acquires the averages of absolute amplitudes from a seismic trace by using three moving time windows before and after each time point [6]. The algorithm of seismic phase monitoring based on the concept of entropy, including the seismic phase picking algorithm of constructing the objective function based on the Akaike information criterion and the mutual information algorithm [7]. Higher-order statistics identify signals by calculating higher-order cumulants of signals under the framework of statistical signal processing [8].

The traditional method of picking P-wave arrival time is relatively simple to calculate, but the recognition performance is usually limited. Either due to the trade-off between false alarms and missed alarms, or due to the trade-off between calculation cost and time sensitivity, the picking accuracy is low and the noise resistance is poor.

The P-wave arrival time picking algorithm based on deep learning can automatically and effectively extract rich features. When using deep learning for P-wave picking, most approaches adopt a segment-based theory [10], [11], [12], which aims to extract the characteristics of noise and seismic signals separately by dividing each waveform trace into noise segments and signal segments. The arrival time is then determined as the boundary between these two parts. In recent years, many researchers have conducted various experiments related to deep learning, including medical image processing, natural language processing, industrial fields and so on. There are also many studies in the field of arrival time picking [13]. For example: (1) The AEnet [14] classifies sample points using CNN and uses curve fitting algorithms and unsupervised clustering algorithms to calculate the P-wave arrival time of sample points. (2) The seismic phase arrival time monitoring algorithm based on the ratio of long and short time window signals [15], [16], which determines the first arrival time of the signal by calculating the energy ratio of the window signal in two time windows [5], [17], [18]. (3) The U-net algorithm completes waveform classification among single-phases, double-phases and noises is completed by setting the probability distribution thresholds of P waves and S waves [19]. The architecture of PhaseNet is based on U-Net, which was originally used for image segmentation in the medical field, and is applied to 1D input data (i.e. time series waveform) to generate P-wave phase probability values. Compared with the original U-Net network structure, PhaseNet has one convolutional layer less in each horizontal layer. The P-wave time picking accuracy is higher than U-Net. (4) Artificial seismic wave simulation algorithm using Generative Adversarial Networks (GAN) [20]. (5) Seismic waveform analysis based on wavelet transform of RNN [21]. Most current automatic phase picking algorithms extract different features of signals and noises to determine whether a seismic phase has arrived [22]. The deep learning-based P-wave arrival time picking algorithms are computationally complex, but they generally achieve higher accuracy compared to traditional algorithms. They exhibit strong noise robustness, making them more resistant to interference from noise. However, the accuracy of these algorithms heavily relies on the boundary recognition process, which can be influenced by the presence of classification outliers. Incorrect classification cases can significantly impact the picking accuracy. Therefore, it is crucial to refine the classification granularity of waveforms and employ more sophisticated models to extract features within these refined categories.

In order to enhance the diagnostic performance in the presence of limited data and strong noise, we propose a multi-time window P-wave arrival time picking algorithm based on the CGAS model. In this algorithm, different convolution kernels are introduced to obtain different feature values. Subsequently, the Squash function is used to improve the dimensionality of the convolution to form a capsule layer, and the feature values are compressed to normalize the data. Additionally, Attention is employed to address the issue of long-distance dependence by extracting the vibration characteristics of waveforms in the system model and calculating the interaction between waveforms. Moreover, GRU reduces the number of gating units and applies GRU to obtain the characteristics of the vibration waveform in the time series, thereby promoting better feature learning. By combining the convolutional neural network layer (CNN), compression function layer (Squash), attention mechanism layer (Attention), and gated recurrent unit layer (GRU), a CGAS deep learning algorithm for picking P-wave arrival times in mining microseismic signals is proposed, which improves the accuracy of P-wave arrival time picking in mining microseismic signals.

The main contributions of the paper are as follows:

1) A multi-time window P-wave arrival time picking algorithm based on the CGAS model is proposed, which achieves high accuracy with only a small amount of data enhanced for model training.
2) The diagnostic performance of the proposed algorithm is analyzed on a data set from a microseismic monitoring system in a mining area under different layer structures and resolution changes. Experimental results show that the proposed model has excellent generalization ability in complex environments compared to other algorithms with limited data.

The rest of this article is organized as follows. Section II introduces the structure of the CGAS deep learning model proposed in this paper. Section III verifies the classification accuracy of the proposed model through analysis of different layer structures and compares the accuracy of different algorithms for arrival time picking under different resolutions.

II. CGAS DEEP LEARNING MODEL FOR P-WAVE ARRIVAL TIME PICKING

A. STRUCTURE OF THE CGAS DEEP LEARNING MODEL

This article obtains P-wave arrival times through sliding windows of microseismic waveforms. The window is classified

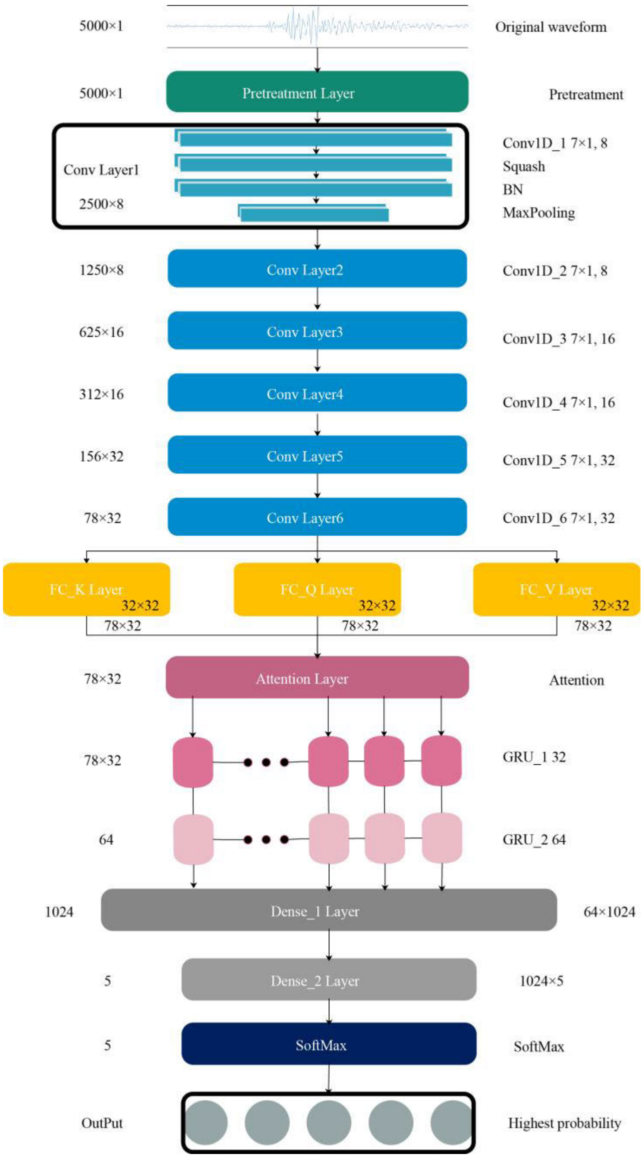

FIGURE 1. CGAS mode structure diagram.

into five categories based on the position of the P-wave arrival time within the sliding window, and the problem is solved as a classification problem. The CGAS model proposed in this article mainly includes convolutional neural network layers (CNN), squash function layers (Squash), attention mechanism layers (Attention), gated recurrent unit layers (GRU), and fully connected layers (FC), as shown in Fig. 1.

In the CGAS model structure, CNN [23] mainly extracts the feature values represented by each point in the vibration waveform. Different convolution kernels will extract different feature values and obtain information about P-wave arrival time from different waveform features.

The Squash function, proposed by Hinton in 2017 [24], is used in capsule neural networks to increase the dimensionality of convolutional layers and compress the feature values, thereby transforming from linear to nonlinear representation. The compression function is shown in Eq.1:

$$v_j = \frac{\left\| s_j \right\|^2}{1 + \left\| s_j \right\|^2} \cdot \frac{s_j}{\left\| s_j \right\|} \tag{1}$$

where j represents the index of the convolutional kernel, s_j represents the output of the j-th dimension of the convolutional layer, v_j represents the compression from the output of the CNN layer. Since the compression function is used, the core of the compression function is to use multiple capsules to pick up the feature information of the waveform instead of a single convolutional kernel, and the picked feature information is more accurate. Then, a group of different convolutional kernels are compressed by the Squash function. In the system model structure of this paper, a capsule layer is formed through different convolutional kernels, and then compressed to have a good normalization effect on the data in the time window [25].

The Attention mechanism is a powerful tool that has been used in various machine learning applications, including natural language processing and computer vision [26]. In this paper, the Attention mechanism is used to extract seismic waveform features in the proposed CGAS model. Unlike traditional convolutional neural networks or recurrent neural networks, the Attention mechanism does not require a large number of parameters and has lower computational requirements. The mechanism works by using Softmax to normalize different feature values and assigns different weights to these feature values to in-crease the proportion of key features in waveform classification. This allows the model to focus on the most relevant information when making predictions, improving its accuracy and efficiency. The Attention mechanism is shown as follows in Eq.2:

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \tag{2}$$

where Q represents the current feature information, K represents all the characteristic information that Q may correspond to in the next step, and V represents the weight, d_k, refers to the dimensions of Q and K, Since the network model used in this paper employs the Self-Attention mechanism, Q, K and V are obtained from the same input data through different fully connected operations. The Self-Attention mechanism is a variant of the attention mechanism that is better at capturing internal correlations of data or features. In the application of Self-Attention mechanism in seismic waveforms, it mainly solves the problem of long-distance dependence by calculating the mutual influence between waveforms.

GRU [27] is a variant of the long short-term memory network (LSTM) [28], which reduces the number of gate units and replaces the input gate, forget gate and output gate with update gate and reset gate to solve the problem of recurrent dependence in recurrent neural networks. Therefore, GRU requires fewer parameters and has faster training speed. In the case of small training samples, the training effect of GRU is better than that of LSTM. In this paper, GRU is used to obtain

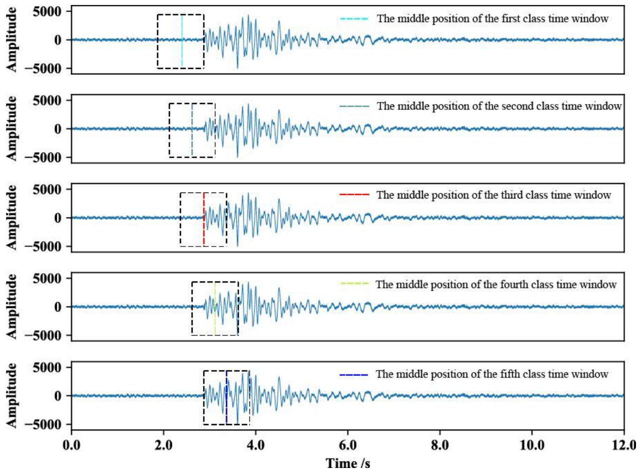

FIGURE 2. Time window classification diagram.

the features of seismic waveforms on the time series, and then the classification is performed through fully connected layers. The detailed parameters of the proposed model are shown in Table 1.

B. CLASSIFICATION OF MICROSEISMIC ARRIVAL TIME PICKING WITH MULTI-TIME WINDOWS

Different from the traditional models for P-wave arrival time picking using long and short time windows [29], this paper proposes a multi-time window algorithm for picking P-wave arrival time in microseismic signals [30], [31]. Firstly, the waveform of the microseismic signal is classified into different types of micro-windows according to the position of the P-wave arrival time within the time window. The classification of the time windows is based on the different states of the time window sliding over the P-wave arrival time, and the specific division algorithm is as follows: the length of the time window is n seconds, and the number of sampling points is set according to the sampling frequency of the station. The training set is divided into 5 categories of sequence windows. The windows slide forward according to a certain step size. Let w denote the manually picked P-wave arrival time and m denote the midpoint position of the window, if $m \in [n/2, w - n/2]$, then this time window belongs to the first category if the relative position of w and m satisfies a certain condition, if $m \in [w - n/2, w - a]$, this time window belongs to the second type of windows, if $m \in [w-a, w+a]$, then this time window is classified as the 3rd type of time window. If $m \in [w + a, w + n/2]$, this window belongs to the fourth category of time windows, if $m \in [w + n/2, l]$, this window belongs to the 5th class of time windows, where l is the length of waveform vibration and a is the dimension of data augmentation. If data augmentation is not required, a = 1. The time window classification of the data set is shown in Fig. 2.

As shown in Fig 2, the relationship between the middle position of the five time windows and the P-wave arrival time determines the classification. It can be seen from the classification that the middle position of the third class time window is the P-wave arrival time to be obtained. Different time windows are marked with different colors on the image.

The classified data set contains 5700 pieces of data. The sampling frequency of the station used in this paper is relatively high. If the data set is small or the signal-to-noise ratio of the microseismic signal is low, data augmentation can be performed [32]. The points before and after the manually picked P-wave arrival time are all regarded as the P-wave arrival time. If the midpoint of the time window m is any point within the range of $(w - a, w + a)$, then all the time windows of this class are regarded as the third class time window. The midpoints of the other several classes of time windows are 2a random points within their respective ranges. The data is augmented by 2a times, and the number of time windows in each class of the data set is the same. For the third type of time window, i.e., the time window where the P-wave arrival time is in the middle position, the 5 points before and after it are all regarded as the P-wave arrival time, and the midpoints of the other several classes of time windows randomly select 10 segments of wave lengths within their respective ranges. The augmented data set has a total of 57000 pieces of data, of which 51300 pieces are used as the training set, 5400 pieces as the test set, and 300 pieces as the validation set. The number of time windows in each class of the data set is the same. The arrival time picking algorithm described in this paper is evaluated.

III. EXPERIMENTAL RESULTS AND ANALYSIS

A. EXPERIMENTAL ENVIRONMENT AND DATA

The experimental data in this paper were obtained from the micro-seismic monitoring system of a mining area in Liaoning province from 2019 to 2020. The vibration waveforms are obtained by the monitoring stations ar-ranged in the microseismic monitoring network in the mining area. The monitoring network consists of eight three-component microseismic monitoring stations, with a span of about 6000m in the east-west direction, 4000m in the north-south direction, and 1000m in the vertical direction, covering a period of one year from December 2019 to December 2020. Unlike microseismic station data, the original sampling frequency of the stations is 5000Hz, and 1140 vibration waveforms were selected by manual picking, with each vibration waveform manually picking the P-wave arrival time.

The evaluation experiment of the proposed model was implemented in Tensorflow2.7.0 and Python3.7.6, run-ning on a device with an Intel(R) Core(TM) i5-10400 CPU @ 2.90GHz (16G RAM) and NVIDIA GeForce RTX 2060. The experimental parameters were set as Batch Size 96, Maximum epochs 100, Optimizer Adam, and Learning rate 0.001.

B. COMPARISON OF CLASSIFICATION RESULT FOR DIFFERENT LAYER STRUCTURES

This study evaluates the model's performance by calculating the Accuracy, Loss, Precision, Recall and F1 score of the test

TABLE 1. Model parameter table.

Layer	Output	Param#	Input	Layer	Output	Param#	Input
Input	(5000,1)	0	/	Conv1	(5000,8)	64	Input
Pool1	(2500,8)	0	Conv1	BN1	(2500,8)	32	Pool1
Conv2	(2500,8)	456	BN	Pool2	(1250,8)	0	Conv2
BN2	(1250,8)	32	Pool2	Conv3	(1250,16)	656	BN2
Pool3	(625,16)	0	Conv3	BN3	(625,16)	64	Pool3
Conv4	(625,16)	1296	BN3	Pool4	(312,16)	0	Conv4
BN4	(312,32)	64	Pool4	Conv5	(312,32)	1568	BN4
Pool5	(312,32)	0	Conv5	BN5	(156,32)	128	Pool5
Conv6	(156,32)	3104	BN5	Pool6	(78,32)	0	Conv6
BN6	(78,32)	128	Pool6	K	(78,32)	1056	BN6
Q	(78,32)	1056	BN6	V	(78,32)	1056	BN6
Attention	(78,32)	0	K,Q,V	GRU1	(78,32)	6636	Attention
GRU2	64	18816	GRU1	Dense1	1024	66560	GRU2
Dense2	5	5125	Dense1	Softmax	5	0	Dense2

results during the training process. Accuracy represents the proportion of correctly predicted waveforms in the automatic pick-up algorithm's predicted waveform among all samples. Recall rate indicates the proportion of all correctly predicted waveforms in the automatic picking algorithm, which is essential in monitoring the integrity of the automatic pick-up algorithm. The F1 score is an index used to measure the accuracy of a binary classification model. It considers both the accuracy and recall of the classification model simultaneously, and can be interpreted as a harmonic average of the model's accuracy and recall. The specific formulas of accuracy, precision, recall and F1 score are shown in Eq.3∼6:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \tag{6}$$

where TP represents the number of times the automatic picking algorithm correctly detected the waveform. Where TN represents the number of times the automatic picking algorithm incorrectly detected the waveform. Where FP represents the number of times the automatic picking algorithm incorrectly detected the waveform as correct. Where FN represents the number of times the automatic picking algorithm missed correctly detected waveforms. This paper adds related network structures such as Squash, Attention, and GRU to the P-wave picking model to verify the degree of improvement in picking accuracy for each layer structure. After using different layer structures, deep learning method-related parameters are subjected to ablation comparison experiments to compare their performance. The structure for comparing deep learning model indicators is shown in Table 2.

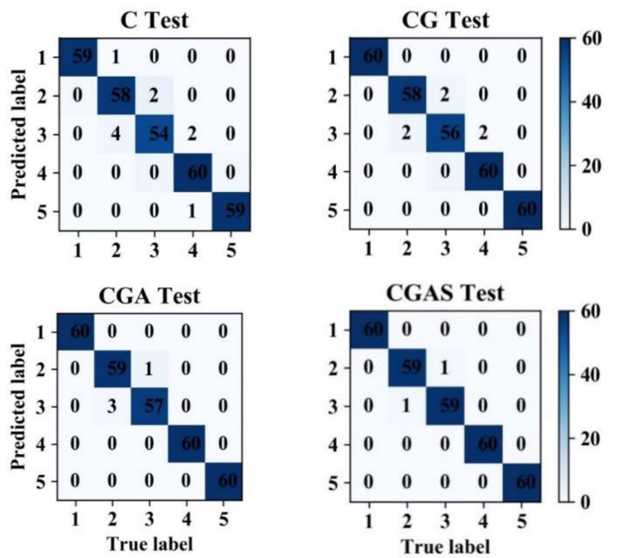

FIGURE 3. Confusion matrix diagrams of classification results.

As can be seen from Table 2, the addition of each network structure leads to an improvement in the relevant indexes of the P-wave arrival pickup model. When all network structures are used, the accuracy and recall rate of the model reach 98.61% and 98.60%, respectively, indicating that each layer structure is effective in classifying the P-wave arrival.

To verify the performance of different layer structures, 300 verification data sets are used, and the confusion matrix diagram of the classification structure is shown in Fig. 3.

The results demonstrate that using only CNN for classification leads to concentrated errors in the second, third,

TABLE 2. Comparison of indicators of deep learning models.

P-wave arrival pickup model	Loss	Accuracy/%	Precision/%	Recall/%	F1%
C	0.0889	96.65	96.67	96.62	96.64
CG	0.0731	96.93	96.93	96.91	96.92
CGA	0.0601	97.78	97.79	97.77	97.78
CGAS	0.0138	98.61	98.66	98.60	98.63

and fourth categories due to similar data characteristics, and six third category data are picked up incorrectly. However, the accuracy of the pick-up model steadily improves with the addition of different layer structures. When all CGAS models are used, only one second category data and one third category data out of the 300 verification set data are identified incorrectly, demonstrating better classification accuracy.

C. COMPARISON OF DIFFERENT ALGORITHMS TO PICK UP WHEN THE TIME COMES

Since the P-wave arrival time picking model in this paper converts the picking problem into a classification problem of waveforms at different stages, the classification situation can be judged by observing the waveform classification trend. In order to compare and analyze the model algorithm in this paper, the STA/LTA [33], U-Net++ [34], Dpick [35], PhaseNet [36] and EQTransformer [37] picking algorithms were compared with the CGAS algorithm. STA/LTA is widely used in seismic data analysis, often as a preliminary step before applying more advanced techniques for event detection and characterization. The U-Net++ follows the advanced idea of deep learning-based end-to-end classification, this paper considers the first-arrival picking of effective microseismic signals as a two classification problem and improves the first-arrival of effective microseismic signals [38]. DPick is an end-to-end approach, and the input is the vertical accelerograms without any preprocessing while the output is the P-wave arrival time [35]. The architecture of U-Net++ and PhaseNet have been modified from U-Net [19] to handle one-dimensional time series data. PhaseNet fully utilizes CNN models, and its structure is relatively clear. It captures temporal signals through an encoding and decoding approach to extract relevant information [39]. EQTransformer improves the performance of the model in each individual task by combining the staged and full-waveform information of the seismic signal using a hierarchical attention mechanism to perform these two related tasks in serie [37]. The real mining microseismic data was used as the data set in this paper, which has a higher sampling frequency compared to seismic station data, approximately 50 times higher. There-fore, there are differences in the P-wave arrival time picking environment, and the picking accuracy needs to be compared and analyzed by classifying two different resolution vibration waveforms [40].

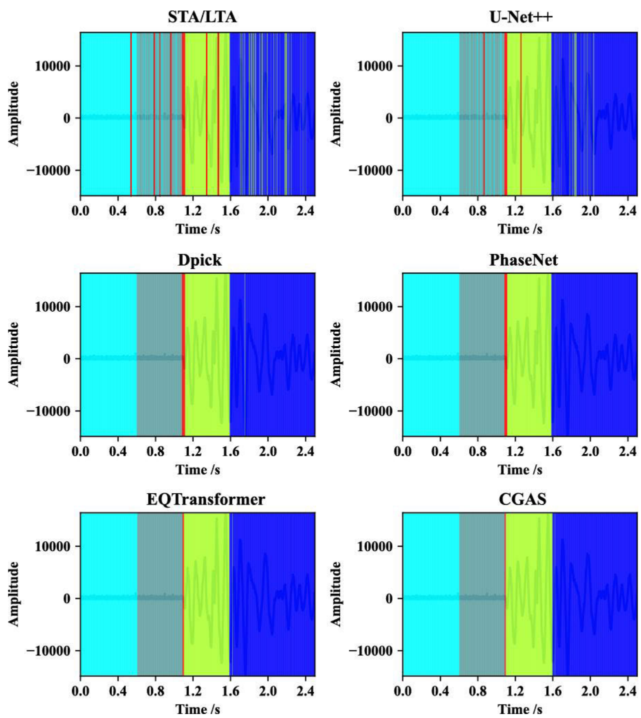

FIGURE 4. Classification of high-resolution vibration waveforms.

1) COMPARISON OF ARRIVAL TIME PICKING RESULTS WITH DIFFERENT ALGORITHMS AT HIGH RESOLUTION

At first, the high resolution seismic waveforms are classified. The test results are shown in Fig. 4. Light blue is the first class time window, gray is the second class time window, red is the third class time window, yellow is the fourth class time window, and the dark blue is the fifth class time window. It can be seen that all six algorithms can accurately classify each type of waveform under high resolution conditions. However, since the P-wave arrival time of each waveform only has 10 sampling points, the larger the span of the third type waveform, the more likely it is that the second and fourth type waveforms are misclassified as the third type. From the figure, it can be seen that the proposed algorithm in this paper has the smallest span for the third type waveform, indicating that the misclassification is minimized, which is beneficial for P-wave arrival time picking.

After classifying the seismic waveforms using the P-wave arrival time picking model pro-posed in this paper, since the defined P-wave arrival time belongs to the third type

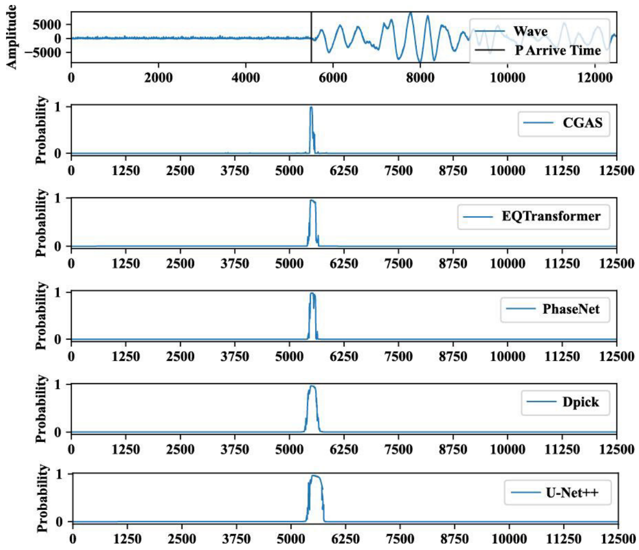

FIGURE 5. High resolution P wave arrival probability diagram.

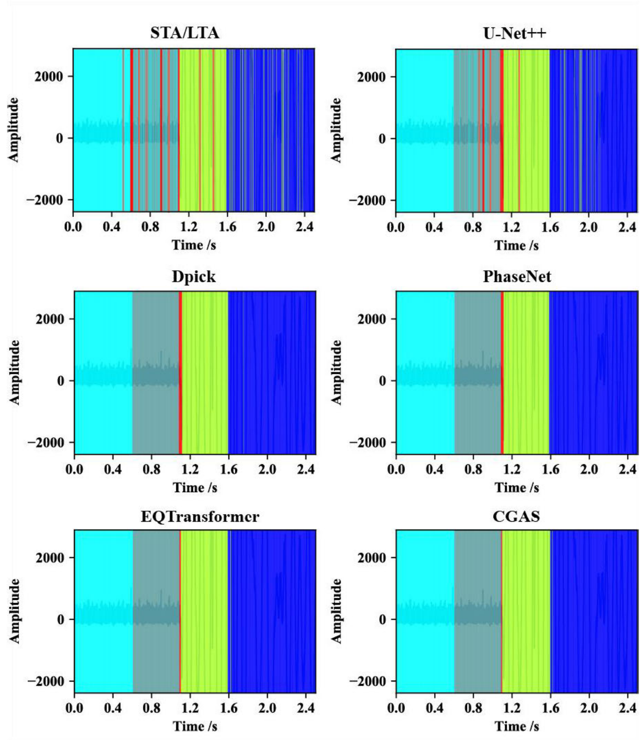

FIGURE 6. Classification of low resolution vibration waveforms.

wave-form, multiple third type waveforms often exist continuously in typical situations. Therefore, the highest probability point is selected as the P-wave arrival time of the seismic waveform for picking. The probability of the P-wave arrival time for each point in the high resolution waveform data is shown in Fig. 5.

STA/LTA method mainly judges the occurrence of microseismic events based on energy comparison, and judges by calculating the ratio between short-term average energy (STA) and long-term average energy (LTA). When the ratio exceeds a preset threshold, it is considered as the trigger of microseismic events, and STA/LTA discrimination of microseismic events is relatively simple.

However, the probability represents the probability distribution of samples belonging to each category, which is a measure of the relative confidence of the model to each category. The STA/LTA method does not directly involve the calculation of probability, so Figure 5 and Figure 7 below are not compared with STA/LTA, only other deep learning models are compared.

2) COMPARISON OF ARRIVAL TIME PICKING RESULTS WITH DIFFERENT ALGORITHMS AT LOW RESOLUTION

In the case of low resolution waveform data, all P-wave arrival time picking models exhibit effective performance. However, in the presence of high levels of noise, the ability of the pickup model to accurately detect relevant features is the primary determinant of model quality. As depicted in Fig. 6, in the case of low resolution, the proposed algorithm demonstrates a high degree of accuracy in classifying vibration waveforms, while other models exhibit poor discrimination and fail to accurately classify the waveforms, leading to significant errors in P-wave arrival time detection. (The color description in Fig.6 is the same as in Fig.4.)

The probability of P-wave arrival at each point of low resolution waveform data is displayed in Fig. 7. Despite the noise interference, the proposed algorithm continues to exhibit a probability distribution of P-wave arrival that remains close to normal distribution. In contrast, other algorithms exhibit errors in detecting P-wave arrival time, often picking up multiple P waves. From a practical standpoint, multiple P-wave detections can be considered a failure to detect P-wave picking.

D. ANALYSIS OF ARRIVAL TIME PICKING ERRORS WITH DIFFERENT ALGORITHMS

In this study, 300 non-training samples were used to test the proposed P-wave arrival time picking algorithm. The P-wave arrival time picking error values of other existing algorithms were also calculated, and the histogram of P-wave arrival time picking errors is shown in Fig. 8.

As shown in Fig. 8, the proposed algorithm has a better error distribution compared to other algorithms. Based on the data in the figure, the picking accuracy is defined as "accurate picking" when the absolute value of the picking error is less than 0.001s, "low error picking" when the absolute value of the picking error is greater than 0.001s and less than 0.002s, "high error picking" when the picking error is greater than 0.002s and less than 0.01s, and "picking failure" when the picking error is greater than 0.01s. The algorithm proposed in this paper has the highest proportion of "accurate picking", which can also prove that the algorithm proposed in this paper is superior to other algorithms.

TABLE 3. Statistics of arrival time-picking accuracy by different algorithms.

P-wave arrival pickup model	P-wave arrival pickup accuracy /%				
	(~-0.01s)	(-0.01s~0)	(0s~0.01s)	(0.01s~)	(-0. 01s~0.01s)
CGAS	4.33	50.33	45.33	0.00	95.67
EQTransformer	2.67	57.33	37.00	3.00	94.33
PhaseNet	3.67	34.00	55.33	7.00	89.33
Dpick	4.33	53.67	35.00	7.00	88.67
U-Net++	7.00	46.33	30.33	16.33	76.66
STA/LTA	22.00	29.67	27.33	21.00	57.00

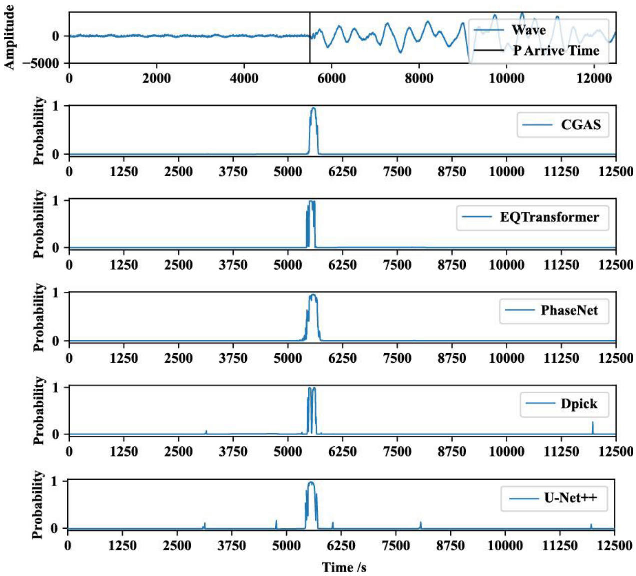

FIGURE 7. Low resolution P wave arrival probability diagram.

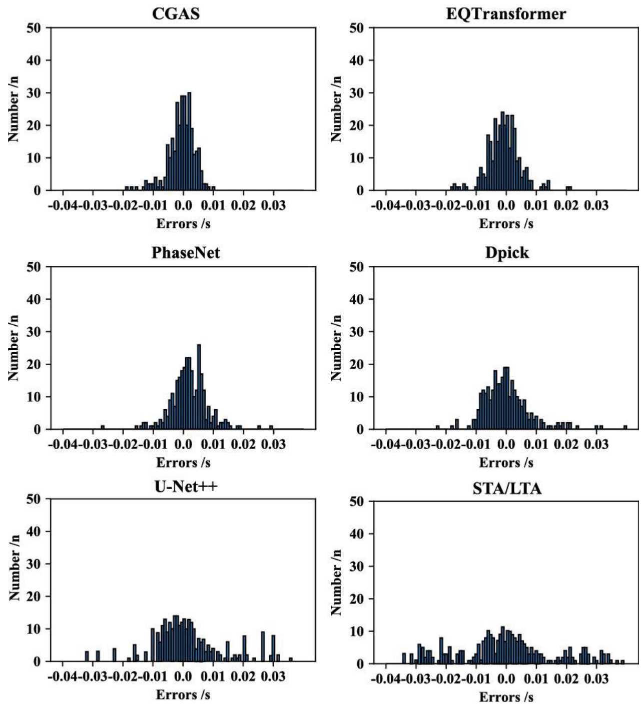

FIGURE 8. Time-picking error histogram of different algorithms.

IV. DISCUSSIONS

The statistics of arrival time-picking accuracy by different algorithms are shown in Table 3. It shows that the proposed algorithm has the highest accuracy in accurate picking. Although the traditional STA/LTA (short-term average to long-term average) method is simple in procedure, it lacks accuracy and performs poorly in picking up data with low signal-to-noise ratio. Additionally, the threshold needs to be manually set. Due to the utilization of multiple branches and decoder paths, the U-Net++ network structure is relatively complex. When dealing with imbalanced data, it may lead to issues such as class bias or incorrect segmentation. Additional processing methods may be required to balance the data or adjust the network weights. As a result, training and inference processes may necessitate more computational resources and time. Dpick is developed based on one-dimensional CNN for interpreting sequential regression. Its structure, model parameters, and the negative noise labels are derived through multiple iterations of training and validation, which may require a considerable amount of time and computational resources to complete. PhaseNet is trained on the substantial catalog of available P and S arrival-times picked by experienced analysts. Unfiltered three-component seismic waveforms are the input to PhaseNet, which is trained to output three probability distributions: P wave, S wave, and noise. The neural network is trained on the target probability distributions of known earthquake waveforms [36]. The performance of EQTransformer is influenced by the training data, and to achieve high accuracy, a large amount of labeled seismic event training data is required.

Obtaining high-quality seismic data and annotating it is a time-consuming and labor-intensive task. From the practical application perspective, the arrival time with an error of less than 0.01s is considered usable in this paper, and the proposed model has a P-wave arrival time picking probability of 95.67%, which is significantly higher compared to other algorithms and mostly concentrated in high-precision P-wave arrival time picking, meeting the requirements for the precision of P-wave arrival time picking in practical applications. According to the comparison results, it is clear that the proposed algorithm certainly promotes the classification accuracy in accurate picking. The superiority of the proposed P-wave arrival time picking algorithm arises from three main aspects:

1) The multi-level convolutional neural network architecture can extract features from signals at different scales, thereby enhancing the noise resistance.

2) The data set in this paper is collected from the real mine seismic data and the number is small, but the accuracy is higher.

3) The results mainly focus on the high precision P-wave arrival time pickup, which meets the requirement of the actual application.

V. CONCLUSION

The traditional P-wave picking algorithms have limitations in terms of poor noise resistance and inefficiency in accurately picking P-wave arrival times. In this paper, a deep learningbased approach is introduced, which proposes a multi-time window P-wave picking algorithm based on the CGAS model, providing a new algorithm for microseismic monitoring in mining. This algorithm utilizes deep learning techniques and trains the model with a small amount of data augmented data to achieve high accuracy in P-wave picking. The CGAS model achieves event detection accuracy and recall rates of over 98% on the test set, with an accuracy of 95.67%. Comparative experiments show that the proposed algorithm outperforms STA/LTA,U-Net++, Dpick, PhaseNet and EQTransformer in terms of accuracy and error, and in practical seismic source location, using the proposed algorithm results in significantly smaller localization errors than other algorithms. In future work, we will consider optimizing the number of parameters to improve the system's processing speed without compromising accuracy and continuously improving the neural network model. The proposed model has potential applications in micro-seismic monitoring and early warning, providing effective practical significance for the analysis of seismic sources in mining areas.

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