An Incremental Framework for Classification of EEG Signals Using Quantum Particle Swarm Optimization

Kaveh Hassani and Won-Sook Lee
School of Electrical Engineering and Computer Science
University of Ottawa
Ottawa, Canada
kaveh.hassani@uottaw.ca and wslee@uottawa.ca

***Abstract*— Classification of electroencephalographic (EEG) signals is a sophisticated task that determines the accuracy of thought pattern recognition performed by computer-brain interface (BCI) which, in turn, determines the degree of naturalness of the interaction provided by that system. However, classifying the EEG signals is not a trivial task due to their non-stationary characteristics. In this paper, we introduce and utilize incremental quantum particle swarm optimization (IQPSO) algorithm for incremental classification of EEG data stream. IQPSO builds the classification model as a set of explicit rules which benefits from semantic symbolic knowledge representation and enhanced comprehensibility. We compared the performance of IQPSO against ten other classifiers on two EEG datasets. The results suggest that IQPSO outperforms other classifiers in terms of classification accuracy, precision and recall.**

Keywords—brain-computer interface; quantum particle swarm optimization; EEG signal calssification

I. INTRODUCTION

A Brain-Computer Interface (BCI), also known as Brain-Machine Interface (BMI), is a communication system that lets the users to interact with electronic devices by means of control signals acquired from electroencephalographic (EEG) activity without engaging peripheral nerves and muscles [1]. The preliminary motivation for BCI research was to develop assistive devices for people with locked-in disabilities. Nowadays, researchers are exploring BCI as a novel anthropomorphic interaction channel for daily applications such as robotics, virtual reality, and games [2].

As shown in Fig. 1, a BCI system recognizes a set of patterns from signals generated by brain activities in five consecutive steps including signal acquisition, signal preprocessing, feature extraction, signal classification and control interface [3]. Signals generated by neural electrochemical activities are captured, amplified and digitalized using electrodes, amplifiers, and A/D convertors, respectively. The acquired signals are filtered to remove both physiological artifacts including electromyography (EMG), electrooculography (EOG), and electrocardiography (ECG), and non-physiological artifacts such as power line noises. The next step is to extract the features of interest from refined signals. These features, found in multiple channels, spatially and temporally overlap with brain signals from other mental activities. Then, classification phase which is the main focus of this paper, is performed to classify the user's intentions using discriminative features. Finally, a control interface interprets the classified signals into high level commands and provides connected devices with those comprehendible commands. Further information regarding signal processing techniques in BCI systems can be found in [4, 5].

Classification of EEG signals is a sophisticated task that determines the accuracy of intention recognition performed by BCI system which, in turn, determines the degree of naturalness of the interaction provided by that system. However, classifying the EEG signals is not a trivial task. In literature, curse of dimensionality and bias-variance tradeoff are mentioned as the main classification problems in BCI applications. EEG signals contain outliers and have very low signal to noise ratio. Also, these signals are often of high dimensionality. Another problem is due to the small size of the training data. Finally, EEG signals are non-stationary and vary over time [6]. A very important aspect of EEG signals is that even for a same subject working on a same mental task, the signals may vary over sessions. In literature, two sources are mentioned for non-stationary characteristics of EEG signals [7]. The first source is the difference between patterns acquired in calibration sessions and patterns emerging during online sessions. The second source is changes in EEG signals due to the changes in subject's concentration, motivation and learning curve. These characteristics of EEG signals necessitate employing incremental classifiers in BCI applications to let the system learn the intention patterns adaptively and online. According to [1], adaptive algorithms are very important for non-invasive and asynchronous BCI systems.

In this paper, we introduce and utilize incremental quantum particle swarm optimization (IQPSO) algorithm for incremental classification of EEG data stream. The proposed algorithm models the classifier as a set of explicit rules whose antecedents are the range of electrode outputs and consequents are mental activities. This model benefits from semantic symbolic knowledge representation. IQPSO modifies the classifier model based on the newly arrived data and extracted knowledge. To do so, it embeds guided initialization and reinforcement steps to the ordinary PSO algorithm to support incremental learning. Moreover, it benefits from quantum behavior that enhances its performance.

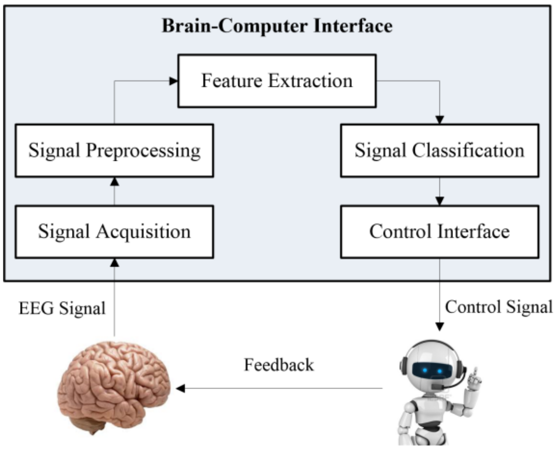

Fig. 1. Schematic of a BCI system.

The paper is organized as follows: in section 2 an overview of related works is presented. Section 3 explains our proposed method. In section 4, evaluation and experimental results are discussed. Finally, section 5 concludes the paper.

II. RELATED WORKS

Lotte, Congedo, Lecuyer, Lamarche and Arnaldi [6] categorized the classification techniques applied in BCI applications to five major categories including linear classifiers (e.g. linear discriminant analysis (LDA) and support vector machine (SVM)), artificial neural networks (ANN) (e.g. multi-layer perceptron (MLP), learning vector quantization neural network (LVQ-NN), RBF neural network, probability estimating guarded neural classifier (PeGNC), finite impulse response neural network (FIRNN), and time-delay neural network (TDNN)), nonlinear Bayesian classifiers (e.g. Bayes quadratic and hidden Markov model (HMM)), nearest neighbor classifiers (e.g. k-nearest neighbors (K-NN)) and ensemble classifiers (e.g. boosting, bagging and stacking). Although many research works have addressed the classification task in BCI applications, only a few have addressed non-stationary properties of the BCI signals.

To address the non-stationary characteristics of EEG signals, a few research works exploited a preprocessing step to enable the static classifiers to be employed in non-stationary environments. Alonso, Corralejo, Álvarez and Hornero [8] proposed an adaptive classification framework in which extracted features from EEG signals are adaptively processed to reduce the small fluctuations between calibration and evaluation data. This step lets the framework to utilize static classifiers to classify the refined features. HSU [9] proposed a two-stage recognition system for continuous analysis of EEG signals. First, wavelet transform and Student's two-sample t-statistics are employed to select and detect the location of the active segment in time-frequency domain, and then multi-resolution fractal feature vectors (MFFVs) are extracted from wavelet data. In second phase, a static SVM classifier is adopted for robust classification of MFFVs.

Some other research works have utilized dynamic classifiers. Among them, incremental SVM is widely applied [10-12]. In some studies, incremental versions of biomimetic pattern recognition (BPR) approach are utilized for online EEG classification task [13-15]. Kai [13] concluded that incremental semi-supervised BPR demonstrates higher accuracy and stability than incremental SVM technique. Furthermore, a few research exploited HMMs for online classification of single trial EEGs during motor imagery tasks [16, 17]. Adaptive discriminant analysis is another class of dynamic classifiers applied to incremental classification of EEG signals [18-20].

As far as the authors' knowledge is concerned, although PSO has been employed to address various issues in BCI applications such as feature selection [21-24], source localization [25, 26], change point detection [27] and adaptive signal filtering [28, 29], it has only been employed as static classifier, in which PSO has mostly been utilized as training algorithm for the neural classifier. PSO-based RBFNN [30] and PSO-based recurrent NN [31] are examples of these hybrid dynamic classifiers. Karait, Shamsuddin and Sudirman [32] introduced a hybrid PSO called adaptive particle swarm negative selection (APSNS) for EEG signal classification. It is noteworthy that as far as the authors' knowledge is concerned, quantum-behaved PSO has only been applied to EEG feature selection task [33, 34].

III. INCREMENTAL EEG CLASSIFICATION

A. Quantum-Behaved PSO Algorithm

PSO algorithm introduced by Eberhart and Kennedy [35] is a swarm intelligence based meta-heuristic approach inspired by the individual and social behavior of flocking birds. PSO is able to reach the globally optimal solution within a few iterations. Akay [36] experimentally showed that PSO is scalable and its processing time grows at a linear rate with respect to the size of the problem. Ordinary PSO algorithm consists of a population of candidate solutions called particles. Each particle is characterized by its position and velocity vectors, and follows its trajectory toward the global optimum based on Newtonian mechanics. In a D-dimensional space, position and velocity vectors of the *ith* particle are depicted as (1). In the same hyperspace, the rules governing the particle's trajectory are depicted in (2) and (3).

$$\vec{x}_i(t) = \left[x_{i1}(t),\ldots,x_{iD}(t)\right]^T, \quad \vec{v}_i(t) = \left[v_{i1}(t),\ldots,v_{iD}(t)\right]^T \tag{1}$$

$$\vec{v}_i(t+1) = w.\vec{v}_i(t) + \varphi_1^T\left(\vec{x}_{pbi} - \vec{x}_i(t)\right) + \varphi_1^T\left(\vec{x}_{gi} - \vec{x}_i(t)\right) \tag{2}$$

$$\vec{x}_i(t+1) = \vec{x}_i(t) + \vec{v}_i(t+1) \tag{3}$$

Where x and v are position and velocity vectors, respectively. w is inertia element utilized to enhance the convergence speed and balance between exploitation and exploration. φ_1 and φ_2 are two positive parameters known as personal and social cognitive factors, respectively. x_{pbi} is the best personal position that *ith* particle have seen so far, and x_g is the position of the best particle seen so far in the swarm history. It has been shown that if the upper limits of personal and social cognitive parameters are selected properly, the position of the *ith* particle converges to position p computed as

(4). Position p can be interpreted as center of gravity towards which particles are careen while their kinetic energy declines [37].

$$p_d = (\varphi_{1d} \times x_{pbd} + \varphi_{2d} \times x_{gd}) / (\varphi_{1d} + \varphi_{2d}) \tag{4}$$

Sun, Feng and Xu [37] proposed a novel version of PSO algorithm (i.e. QPSO) in which particles obey the rules governing quantum mechanics rather than Newtonian mechanics. In this approach, the quantum state of a particle is expressed by a wave function based on Schrodinger's uncertainty principle. Also, the trajectory of a particle is modeled using quantum Delta potential well model. In this model, it is assumed that a particle moves in a Delta potential well in search space, of which the center is point p calculated by (4). In order to compute the fitness of an individual particle, its exact position is needed. However, in quantum model, only the probability density function of the position is available. To address this issue, Monte Carlo method is applied to simulate the measurement process from wave function. Using this technique, particles' estimated position vector is governed by the rule depicted in (5). Sun, Feng and Xu [37] experimentally showed that QPSO can outperform ordinary PSO in minimizing the benchmark functions.

$$x_{id} = p_d \pm \frac{|x_{id} - p_d| \ln(1/u)}{g} \tag{5}$$

u is a random number between 0 and 1, and g is a control parameter greater than $ln\sqrt{2}$.

B. Incremental PSO Algorithm

In order to provide our proposed approach with incremental learning capabilities, we adopted the study conducted by Hassani and Lee [38] in which they proposed a framework for incremental and parallel classification rule discovery using PSO algorithm. Their proposed framework consistently receives training data chunks and modifies its classification model in a way that it can address both old and new data. To do so, they have applied two modifications to the ordinary PSO algorithm. First, instead of initializing the swarm randomly, they employ extracted rules from processed data stream to initialize the individuals. This non-random initialization is performed using a roulette wheel which selects the rules to be copied to the individuals. Those rules with higher support count (i.e. number of instances they cover) have better chance to be overwritten in initial population. Second, they embedded a reinforcement step into the conventional PSO algorithm. This step utilizes a tournament selection method to select one candidate particle from swarm and one candidate rule from classification rule set. In order to select the candidate particle, m particles are selected randomly (i.e. m is fairly smaller than swarm size), and the weakest of them is considered as the candidate. On the other hand, the same method is used to select the candidate rule. However, the candidate rule is defined as the rule with highest support count among the selected rules. Finally, the selected rule is overwritten on the selected particle to reinforce the swarm. These two modifications lets the PSO to exploit the previously extracted compact knowledge as the representative of the old data which, in turn, allow to build the classification model only by processing new data in a way that the model covers both old and new data.

C. IQPSO Algorithm for EEG classification

We utilize an incremental platform similar to the framework introduced by Hassani and Lee [38]. As shown in Fig. 2, this framework consists of training and testing components. The framework continuously receives EEG signals. Training component utilizes temporal windows of the streamed signals as training data chunks, whereas testing component accumulates them in a data repository. In this framework, IQPSO algorithm consistently modifies the classification model in a way that the model adapts to the distribution of new data chunks while it is consistent with the distribution of old data. To validate the model, it is tested by samples of both old and new data.

IQPSO represents the classification model as a set of explicit IF-THEN prediction rules which benefit from semantic symbolic knowledge representation and enhanced comprehensibility. Antecedents of each rule are range of electrode outputs and consequents are mental activities. We apply Michigan approach [39] as individual representation scheme, where each individual represents a single classification rule. The individual representation is depicted in (6).

$$x_j = \left\langle \left[E^L_{j,1}\right]\left[E^U_{j,1}\right]\left[E^L_{j,2}\right]\left[E^U_{j,2}\right] \ldots\ldots \left[E^L_{j,i}\right]\left[E^U_{j,i}\right] \ldots\ldots \left[E^L_{j,n}\right]\left[E^U_{j,n}\right]\left[C^k_j\right] \right\rangle \tag{6}$$

In this representation, x_j is the position vector of the *jth* particle. $E^L_{j,1}$ and $E^U_{j,1}$ refer to the lower and upper bounds of the *ith* electrode in *jth* particle, respectively. n is the number of electrodes utilized in process. It is noteworthy that n is equal or smaller than the number of physical electrodes due to the feature selection phase which may omit the outputs of some electrodes. Finally, C^k_j represents the *kth* mental activity. If n electrodes are selected, the length of individual particle will be $2n+1$. The corresponding rule represented by the particle shown in (6) is depicted in (7).

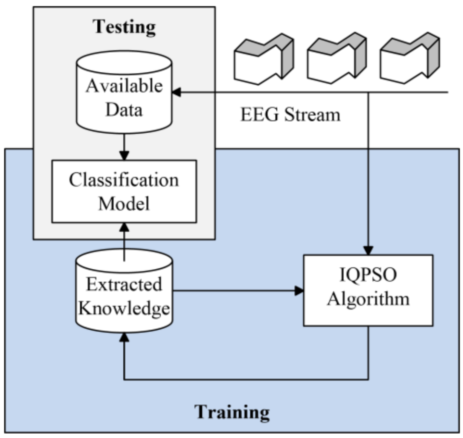

Fig. 2. Schematics of the proposed incremental platform.

$$IF\ (E^{L}_{j,1} \le O_1 \le E^{U}_{j,1}\ AND \ldots AND\ E^{L}_{j,n} \le O_n \le E^{U}_{j,n})\ THEN\ C^{k}_{j} \quad (7)$$

The rule depicted in (7) indicates that if the output of the first electrode, O_1, is between $E^{L}_{j,1}$ and $E^{U}_{j,1}$, and the output of the second electrode, O_2, is between $E^{L}_{j,2}$ and $E^{U}_{j,2}$, and this goes on up to the *nth* electrode, then the subject's intention is the *kth* mental activity within the predefined finite set of mental activities. It is noteworthy that it is not practical to use the exact values of electrode outputs within the rule antecedents. Moreover, it should be noted that if the value of $E^{L}_{j,i}$ is smaller than the minimum value that can be generated by *ith* electrode, or the value of $E^{U}_{j,i}$ is greater than the maximum possible value of the *ith* electrode, the corresponding boundary is considered as "do not care". As an example, if the possible minimum and maximum values for the *ith* electrode are 0.1 and 1, respectively, and the upper and lower bounds of the corresponding electrode is determined as 0.05 and 1.1, then the electrode is considered as "do not care". The particle's fitness is determined by its *F-Score* measure as depicted in (8).

$$F-Score = \frac{2 \times precision \times recall}{precision + recall} \quad (8)$$

Precision and recall (i.e. sensitivity) are computed by (9).

$$precision = \frac{TP}{TP+FP} \quad , \quad recall = \frac{TP}{TP+FN} \quad (9)$$

Where *TP* refers to the number of positive data objects that are correctly classified, *FP* is the number of negative instances that are incorrectly classified, and *FN* is the number of positive objects mislabeled as negative.

We propose the IQPSO algorithm as depicted in (10).

$Function\ \ IQPSO$ (10)

- $Initilaize\ \ swarm\ (extracted\ \ rules)$
- $For\ \ j = 1\ \ to\ \ iteration\ \ N$
  - $For\ i = 1\ \ to\ Population\ Size\ M$
    - $If\ \ F\text{-}Score\ (x_i) > F\text{-}Score\ (p_i)\ \ Then\ \ \ p_i = x_i$
    - $p_g = Max\ (p_i)$
    - $For\ d = 1\ \ to\ Dimension\ D$
      - $\varphi_1 = rand(0,1), \quad \varphi_2 = rand(0,1)$
      - $p = (\varphi_1 \times p_{id} + \varphi_2 \times p_{gd})/(\varphi_1 + \varphi_2)$
      - $u = rand\ (0,1)$
      - $L = (1/g) \times |x_{id} - p|$
      - $If\ \ rand(0,1) > 0.5\ \ Then\ \ x_{id} = p - L \times \ln(1/u)$
      - $Else\ \ x_{id} = p - L \times \ln(1/u)$
    - End
  - End
  - $Reinforce\ \ swarm\ (extracted\ \ rules)$
- End
- $Return\ \ (new\ rules)$

End

In the proposed algorithm, roulette wheel selection method is applied to directly overwrite previously extracted rules to the initial swarm. Rules with higher support count have more chance to be reused as initial individuals. After guided initialization step, quantum-behave PSO discussed in section III.A takes over. In each iteration, the reinforcement mechanism is applied to substitute the week individuals with strong extracted rules. This mechanism utilizes a tournament selection method to replace the particles with low support count with rules that have higher support count. It is noteworthy that the *F-Score* measure depicted in (8) is used to evaluate the particles' fitness. Finally, after a few iterations, new classification rules are returned. These rules cover both old and new data.

IV. EXPERIMENTAL RESULTS

In order to evaluate the performance of our proposed approach, we applied it to two EEG datasets acquired from UCI machine learning repository. The first dataset, planning/relaxing dataset concerns with the classification of two mental stages from recorded EEG signals: planning (i.e. during imagination of motor act) and relaxing states. This dataset consists of 13 attributes representing values of eight EEG electrodes (C3, C4, P3, P4, F3, F4, T3, and T4), two reference electrodes (A1 and A2), ground electrode, and two EOG electrodes. The class attribute is a binary feature that indicates the subject's current mental state (i.e. whether relaxing or planning). This dataset contains 182 data instances. The second dataset, EEG eye state dataset, concerns with the classification of the subject's eyes state (i.e. whether close or open). The dataset consists of 14 attributes representing the values acquired from 14 electrodes (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4). Furthermore, the dataset contains a binary attribute which indicates whether the subject's eyes are open or close. The dataset consists of 14980 data instances.

In order to conduct a comparative study on the performance of IQPSO algorithm and other classifiers, we applied six classifier categories (i.e. five mentioned categories in [6] plus a meta-heuristic category) to datasets. As a representative of linear classifiers, we used SVM classifier. For ANN category, MLP and RBF neural networks are utilized. Naïve Bayesian and K-NN classifiers are employed as representatives of Bayesian and nearest neighbor (NN) classifier categories, respectively. As ensemble classifiers, we exploited AdaBoost, bagging and stacking classifiers. Finally, incremental genetic algorithm (IGA), Incremental PSO (IPSO) and our proposed method, IQPSO are used as meta-heuristic classifiers. It is noteworthy that the first five classifier categories are utilized as static classifiers. Therefore, we used batch training paradigm through their learning process. In order to evaluate the performance of the static classifiers, we exploited WEKA data mining software which provides the researchers with stable implementations of the mentioned classifiers. The parameters of these classifiers are set on default values of the WEKA.

On the other hand, the classifiers within meta-heuristic category are all incremental classifiers. We applied the techniques proposed by Bakirli, Birant and Kut [40], and Hassani and Lee [38] to implement the IGA and IPSO classifiers, respectively. These classifiers are implemented in visual C#. Net programming language. In order to provide the meta-heuristic classifiers with data stream, we split the datasets to a few data chunks in chronological order considering predetermined window sizes, and then send them to the classifiers in consecutive time steps. We consider 25% of the first dataset size (45 instances), and 1% of the second dataset size (150 instances) as temporal window sizes. For all three meta-heuristic classifiers, the population size and iteration number are set to 25 and 100, respectively. In IPSO, personal and social cognitive parameters are both set to 2. Also, dynamic inertia term as depicted in (11) is utilized.

$$w = w_{\max} - \left(\frac{w_{\max} - w_{\min}}{T} \times t \right) \tag{11}$$

Where w is inertia, w_{max} and w_{min} are inertia boundaries, T is the total number of iterations, and t is the current iteration. In experiments, the inertia boundaries are set to 0.1 and 0.9. For our proposed algorithm, IQPSO, minimum support count is set to 1% of the size of the current windows size. Also, the control parameter g is set to $2ln\sqrt{2}$.

In order to have a quantitative analysis of the performance of the mentioned classifiers, we considered classification accuracy, precision, recall, F-score and processing time as evaluation measures. Accuracy is computed by dividing the summation of true positives and true negatives to the total number of instances. F-score, precision and recall are calculated using (8) and (9), respectively. These measures are acquired using 10-fild cross validation technique. Processing time is the average required time for building the classification model for each fold. Evaluation results are shown in Table I.

In terms of processing time, as indicated in Table I, K-NN, Naïve Bayesian, and stacking classifiers outperform the others regarding the first dataset. Also, for the second dataset, K-NN classifier shows the least processing time. Considering both datasets, it can be concluded that K-NN classifier outperforms other classifiers in terms of processing time. Moreover, as results indicate, SVM, AdaBoost, stacking, and IQPSO classifiers reach the best classification performance in terms of accuracy, precision, recall and F-score measures regarding the first dataset. However, for the second dataset, K-NN and IQPSO outperform other classifiers. All in all, the results suggest that:

- IQPSO demonstrates acceptable processing time for online learning which can be enhanced by using parallel processing techniques.
- IQPSO is the only classifier that achieves the maximum classification accuracy, precision, recall and F-score measures in both datasets.

V. CONCLUSION

In this paper, for the first time, we introduced and utilized incremental quantum particle swarm optimization (IQPSO) algorithm for incremental classification of EEG data stream. IQPSO builds the classification model as a set of explicit rules which benefits from semantic symbolic knowledge representation and enhanced comprehensibility. The proposed algorithm benefits from incremental learning capability and quantum-oriented enhancements, simultaneously. We compared the performance of IQPSO against ten other classifiers that have been applied to BCI applications on two EEG datasets. The results suggest that IQPSO outperforms other classifiers in terms of classification accuracy, precision and recall. Also, it demonstrates acceptable processing time for online learning. As future works, we are planning to boost the processing time by utilizing parallel processing techniques. Furthermore, we are planning to enhance the algorithm to deal with the real world BCI applications by embedding semi-supervised learning capabilities.

TABLE I. COMPARISON BETWEEN PSO AND OTHER CLASSIFIERS REGARDING CLASSIFICATION PERCISION

Dataset	**Measure**	**Classifier**										
		Linear	**ANN**		**Bayesian**	**NN**	**Ensemble**			**Meta-heuristic**		
		SVM	***MLP***	***RBF***	***Naïve***	***K-NN***	***AdaBoost***	***Bagging***	***Stacking***	***IGA***	***IPSO***	***IQPSO***
I	***Accuracy***	**0.713**	0.624	0.646	0.669	0.619	**0.713**	0.696	**0.713**	0.621	0.696	**0.713**
	Precision	**0.713**	0.702	0.697	0.709	0.734	**0.713**	0.710	**0.713**	0.693	0.710	**0.713**
	Recall	**1.000**	0.822	0.891	0.907	0.729	**1.000**	0.969	**1.000**	0.815	0.969	**1.000**
	F-score	**0.832**	0.757	0.782	0.796	0.732	**0.832**	0.820	**0.832**	0.749	0.820	**0.832**
	Process time	0.09s	1.31s	1.28s	**0.01s**	**0.01s**	0.05s	0.13s	**0.01s**	4.12s	1.57s	1.48s
II	***Accuracy***	0.551	0.548	0.559	0.468	**0.968**	0.668	0.892	0.551	0.614	0.892	**0.968**
	Precision	0.753	0.539	0.554	0.519	**0.968**	0.674	0.892	0.304	0.652	0.892	**0.968**
	Recall	0.551	0.548	0.559	0.468	**0.968**	0.668	0.892	0.551	0.614	0.892	**0.968**
	F_2	0.392	0.536	0.462	0.388	**0.968**	0.655	0.892	0.392	0.632	0.892	**0.968**
	Process time	6.55s	145s	98s	0.28s	**0.02s**	3.5s	11.3s	0.14s	15.23	5.20	5.12

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