

Multiclass SVM with Kernel Optimization for Schizophrenia Subtype Classification Using Clinical Symptom Records

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Submitted : Feb 19, 2026 | Accepted : Mar 4, 2026 | Published : Apr 2, 2026

Abstract: Schizophrenia is a mental disorder that affects about 0.3% of the world population. It is characterized by a wide range of symptoms that form several subtypes. Overlapping symptoms and subjective clinical assessments may reduce consistency and make subtype classification challenging. Machine learning algorithms that use patients' medical records offer a potentially objective approach for subtype classification. This study aims to classify four schizophrenia subtypes: paranoid, catatonic, undifferentiated, and residual, based on subtype labels recorded in the hospital using a multiclass SVM approach with kernel optimization. The dataset consists of 218 medical records of schizophrenia patients with 25 binary symptom variables used as input features. SVM was trained using two multiclass approaches, namely OAO and OAA. Evaluation was performed using five-fold stratified cross-validation. Performance was calculated using accuracy, macro-precision, macro-recall, and macro F1-score. Optimal performance was achieved using the OAA approach with an RBF kernel at $C = 10$ and $\gamma = 0.1$. This configuration achieved an accuracy, macro-precision, macro-recall, and macro F1-score of 0.89, 0.90, 0.86, and 0.87, respectively. These results show that the multiclass approach, kernel functions, and parameter configuration influence classification performance. The proposed model may serve as a screening or decision-support tool to assist subtype identification based on clinical symptom records.

Keywords: Clinical Symptom Records; Multiclass SVM; One-Against-All; RBF Kernel; Schizophrenia;

INTRODUCTION

Schizophrenia is a mental disorder characterized by delusions, disorganized speech, hallucinations, and troubles with executive functioning (Velligan & Rao, 2023). Affecting about 0.3% of the world population, it remains one of the most impairing mental health conditions in its acute state (World Health Organization, 2025). Although prevalence rates are relatively stable worldwide, individuals with schizophrenia often experience social troubles, including unemployment, poverty, homelessness, and reduced life expectancy (Anwar et al., 2025). The etiology of schizophrenia is considered multifactorial, involving a combination of genetic and environmental factors (Faden & Citrome, 2023). This disorder usually begins during adolescence or early adulthood and is marked by functional deterioration, a chronic course, and an increased risk of developing other health problems, such as cardiovascular disease, chronic obstructive pulmonary disease, obesity, and diabetes (Tandon et al., 2024).

Schizophrenia has a wide range of symptoms and is classified into several subtypes according to the prominent symptoms exhibited by individuals. The International Classification of Diseases 10th Revision (ICD-10) classifies schizophrenia into paranoid, hebephrenic, catatonic, undifferentiated, post-schizophrenic depression, residual, simple, other, and unspecified (Lim et al., 2025). Nevertheless, the 11th version (ICD-11) later removed this subtype categorization to enhance clinical utility and align more closely with DSM-5 (Valle, 2020). Despite this revision, ICD-10 is still widely used to describe patient diagnoses and to code medical records (Silva, Duque, Macedo, & Mendes, 2024).

Schizophrenia diagnoses at the hospital where this study was conducted are recorded using the ICD-10 subtype labels. Accurate classification of these subtypes is important because overlapping symptoms across subtypes complicate diagnosis and increase the risk of misclassification, which may affect the appropriate treatment

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(Prambudi, Susanto, & Sari, 2025). Additionally, the subjective nature of psychiatric assessment may cause differences in diagnosis among clinicians, as interrater reliability in schizophrenia diagnosis is only moderate, which could lead to misdiagnosis (Goel, 2025). These problems highlight the need for a data-driven approach to improve the accuracy and consistency of subtype classification.

Machine learning algorithms are growing increasingly popular for developing data-driven classification systems, particularly in healthcare. One well-known algorithm that has proven effective in classification tasks, especially with complex data, is Support Vector Machine (SVM) (Yuliana, Robet, & Hoki, 2026). SVM was first developed for binary classification but has been extended to multiclass classification using approaches such as One-Against-One (OAO) and One-Against-All (OAA). In addition, kernel functions enable SVM to handle non-linear classification problems by mapping input data into a high-dimensional feature space (Purnami et al., 2025). This ability makes SVM suitable for analyzing complex medical data characterized by multiple classes and non-linear relationships among clinical features.

Most prior machine learning studies in schizophrenia research have focused primarily on binary classification, such as distinguishing patients with schizophrenia from healthy individuals (Soria et al., 2023). Other studies have emphasized detection or general diagnosis rather than subtype classification and usually rely on high-cost data acquisition and specialized equipment, such as neuroimaging or electrophysiological data (Miras, Ibáñez-Molina, Soriano, & Iglesias-Parro, 2023; Tavakoli, Rostami, Shalhaf, & Nazem-Zadeh, 2025). Some studies have applied algorithms such as Fuzzy K-Nearest Neighbor (FKNN) and Random Forest using clinical symptom information from medical records that are more accessible in routine clinical settings (Prambudi et al., 2025; Sunaryo, Somantri, & Triwiyatno, 2025). However, studies that specifically examine schizophrenia subtype classification using multiclass SVM remain limited. Although multiclass SVM is widely used, systematic comparisons between OAO and OAA approaches across different kernel functions and parameter configurations for schizophrenia subtype classification using clinical symptom data are rarely reported.

Therefore, the present study proposes a multiclass SVM model to classify four schizophrenia subtypes: paranoid, catatonic, undifferentiated, and residual, using clinical symptom data documented in hospital medical records. This study evaluates different multiclass SVM approaches, kernel functions, and parameter configurations to determine the most suitable model for schizophrenia subtype classification. This study does not aim to redefine the nosology of schizophrenia but instead to classify the subtype labels already documented in medical records.

LITERATURE REVIEW

Machine learning has been widely used in healthcare to analyse medical data for prediction and classification tasks, particularly to support disease diagnosis (An, Rahman, Zhou, & Kang, 2023). In mental health research, machine learning algorithms have been applied to classify schizophrenia by distinguishing patients from healthy individuals (Miras et al., 2023; Shanarova et al., 2023; Soria et al., 2023). These studies provide promising classification performance and show the potential of machine learning as a supportive tool in psychiatric assessment. However, the majority of current studies focus on binary classification, while schizophrenia subtype classification involving multiple classes has received less attention.

Numerous studies have performed schizophrenia classification using neuroimaging and electrophysiological data. Approaches based on MRI and EEG have been implemented using algorithms such as SVM, Logistic Regression, and KNN (Desiawan & Solichin, 2024; Nisa & Wibisono, 2023; Tavakoli et al., 2025). These datasets provide detailed information about brain activity and structure, which can support classification. Nevertheless, the need for specialized equipment and more complex preprocessing may limit their routine use in clinical settings.

Clinical symptom information documented in hospital medical records provides a more practical alternative. Previous studies have used clinical features to classify schizophrenia and mental disorder subtypes using several algorithms, such as KNN, FKNN, and Random Forest (Kiram, Darnila, & Sahputra, 2025; Prambudi et al., 2025; Sunaryo et al., 2025). These studies indicate that clinical features have demonstrated promising results in subtype classification for mental disorders, including schizophrenia.

SVM has been applied in several schizophrenia classification studies (Desiawan & Solichin, 2024; Hartini & Rustam, 2020; Tavakoli et al., 2025). Previous studies show that SVM performance may vary depending on parameter settings such as C , γ , and the selected kernel function (Desiawan & Solichin, 2024). In multiclass problems, different strategies such as OAO and OAA can lead to different classification outcomes (Purnami et al., 2025). These studies suggest that SVM performance depends on the selected multiclass approach, kernel function, and parameter configuration.

Many medical datasets exhibit class imbalance, a condition in which class distributions are uneven (Guido, Ferrisi, Lofaro, & Conforti, 2024). In such conditions, models may become biased toward majority classes. Recent studies have shown that applying class weights during training can help address this issue by giving more importance to minority classes (Razali, Arbaiy, Lin, & Ismail, 2025). In imbalanced multiclass settings, accuracy alone may not represent reliable performance. Therefore, macro F1-score is appropriate because it evaluates each class equally and then calculates the average performance (Lee, Braet, & Springael, 2024). Stratified K-Fold

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Cross-Validation (SKCV) is often used because it maintains class proportions in each fold (Widodo, Brawijaya, & Samudi, 2022), thereby enabling more consistent evaluation across classes.

Based on this background, the present study evaluates multiclass SVM for schizophrenia subtype classification using clinical symptom data from medical records. The study compares OAO and OAA approaches, different kernel functions, and parameter configurations. This study uses macro F1-score as the main evaluation metric. Class weighting and stratified validation are applied to reduce bias from imbalanced subtype data.

METHOD

This section describes the dataset and the classification method applied in this study. It also explains how the data were prepared and how different kernel functions and parameter configurations were evaluated. The proposed schizophrenia subtype classification has four main steps: data collection, data preprocessing, classification, and performance evaluation. The overall workflow of the study is presented in Figure 1.

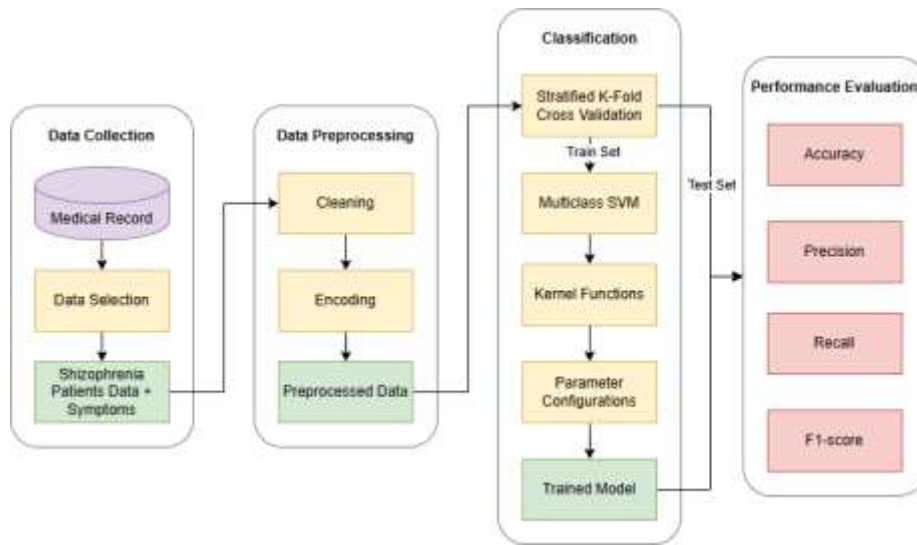


Figure 1. Workflow of the proposed schizophrenia subtype classification

Data Collection

This study used secondary anonymized medical record data obtained from RSJD Atma Husada Mahakam. Institutional permission to access and use the data was obtained prior to the study. The dataset comprised 218 records of patients diagnosed with schizophrenia and classified into four subtypes: paranoid, catatonic, undifferentiated, and residual based on subtype labels recorded in the hospital. The distribution of each subtype is shown in Table 1.

Subtype	Frequency	Percentage (%)
Paranoid	89	40.8
Catatonic	18	8.3
Undifferentiated	89	40.8
Residual	22	10.1

Medical records were selected based on complete symptom information and confirmed subtype diagnosis (ICD-10). Records with incomplete symptom information or unclear subtype diagnoses were excluded. The dataset included patient code, age, gender, clinical symptoms, and subtype. All records were anonymized and contained no identifiable personal information to ensure patient confidentiality. Although age and gender were included in the dataset, this study focused solely on clinical symptom variables to maintain consistent input features for classification. A sample of the collected records is presented in Table 2.

Table 2. Sample Medical Records of Schizophrenia Patients

Patient Code	Age	Gender	Symptoms	Subtype
P1	40	M	Hallucinations, labile mood, social withdrawal, agitation, harming others	Undifferentiated

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Patient Code	Age	Gender	Symptoms	Subtype
P2	33	F	Hallucinations, agitation, suicide idea, reluctance to communicate, disturbing others, hostility, talking to oneself	Undifferentiated
P3	40	F	Hallucinations, confusion, labile mood, sleep disturbance, disordered speech	Undifferentiated
⋮	⋮	⋮	⋮	⋮
P216	30	M	Hallucinations, auditory hallucination, aggressive, poor self-care	Paranoid
P217	64	M	Auditory hallucination, disorganized behavior, confusion, labile mood, disordered speech, suicide idea, lack of motivation	Undifferentiated
P218	31	M	Anxiety, blunted affect, sleep disturbance, daydreaming, lack of motivation	Undifferentiated

Data Preprocessing

Before classification, several preprocessing steps were applied to prepare the data. The dataset in Table 1 needed to be converted to numerical form to serve as input to the classification process. This study used 25 predefined schizophrenia symptoms obtained from an interview with a hospital psychiatrist. Each symptom was assigned a code from G01 to G25, as presented in Table 3.

Table 3. Schizophrenia Symptom List with Codes

Code	Symptom
G01	Thought echo or thought broadcasting
G02	Delusions
G03	Echolalia
G04	Echopraxia
G05	Hallucinations
G06	Persecutory delusion
G07	Auditory hallucination
G08	Disorganized behavior
G09	Psychomotor disturbance or waxy flexibility
G10	Uncontrolled movement
G11	Confusion
G12	Labile mood
G13	Excessive fear or anxiety
G14	Labile affect or blunted affect
G15	Suspiciousness or unusual idea
G16	Negative beliefs
G17	Aggressive, unfriendly attitude, inappropriate behavior, or disordered speech
G18	Emotional numbness, loss of interest, or suicide idea
G19	Reluctance to communicate
G20	Social withdrawal
G21	Agitation, daydreaming, restlessness, or sleep disturbance
G22	Lack of motivation, slowed movement, or difficulty in planning goals
G23	Poor self-care, self-harm, harming others, or disturbing others
G24	Tension, hostility, thought blocking, or thought insertion
G25	Bizarre behavior (grimacing, inappropriate laughter, or talking to oneself)

Symptom identification was performed using case-insensitive text matching based on the predefined symptom terms listed in Table 3. For each symptom code, the corresponding term was searched within each patient's recorded clinical symptoms. Some codes were associated with more than one term (e.g., “excessive fear” or “anxiety”). If a term was found, the related code was assigned a value of 1 (present); otherwise, it was assigned a value of 0 (absent). The symptom terminology in the dataset was consistent with the predefined symptom list obtained from the psychiatrist. Therefore, no additional synonym expansion or negation handling was required.

This process transformed textual symptom data into 25 binary variables representing symptom presence, which served as input for classification. Encoded features were assigned equal weight to ensure consistency and avoid subjective weighting. A subset of 30 medical records was manually reviewed by comparing documented symptoms

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with encoded features. Subtype labels were converted into numerical values using label encoding: 0 for catatonic, 1 for paranoid, 2 for residual, and 3 for undifferentiated. The preprocessed dataset is presented in Table 4.

Table 4. Preprocessed Schizophrenia Dataset

Patient Code	G01	G02	G03	G04	G05	...	G21	G22	G23	G24	G25	Subtype
P1	0	0	0	0	1	...	1	0	1	0	0	3
P2	0	0	0	0	1	...	1	0	1	1	1	3
P3	0	0	0	0	1	...	1	0	0	0	0	3
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
P216	0	0	0	0	1	...	0	0	1	0	0	1
P217	0	0	0	0	1	...	0	1	0	0	0	3
P218	0	0	0	0	0	...	1	1	0	0	0	3

Classification

The SVM algorithm was used as the classification approach, given that previous studies have demonstrated its strong performance in medical data classification (Hamdani, Hatta, Puspitasari, Septiarini, & Henderi, 2022; Qaiser et al., 2024; Ramadhan, Asrianda, & Risawandi, 2025). SVM works by finding an optimal hyperplane that separates classes through maximizing the margin between the closest data points, known as support vectors (Jain & Kumar, 2022). The dataset used in this study comprises four classes. Therefore, classification was implemented using two multiclass SVM approaches: OAO and OAA. The OAO approach creates a hyperplane for each pair of classes, resulting in multiple binary classifiers (e.g., six classifiers are formed when four classes are used). The OAA approach, on the other hand, creates one hyperplane for each class against all the other classes. This indicates that the number of classifiers equals the number of classes (Abdelfattah et al., 2023).

Kernel functions were used to address possible nonlinear relationships among clinical symptom features. This study evaluated four kernel functions to find the most optimal classification model, namely linear, polynomial, radial basis function (RBF), and sigmoid kernels as defined in (1–4) (Yamasari et al., 2023):

$$K(x, z) = x^T z \quad (1)$$

$$K(x, z) = (1 + x^T z)^d \quad (2)$$

$$K(x, z) = \exp(-\gamma \|x - z\|^2) \quad (3)$$

$$K(x, z) = \tanh(\gamma x^T z + r) \quad (4)$$

where x and z are input data points, d is the polynomial degree, r is the sigmoid parameter, and γ is the gamma parameter. Parameter configuration was performed by adjusting the regularization parameter C , which controls the trade-off between maximizing margin and minimizing classification error. The C parameter was tested at values of 0.1, 1, and 10. The γ parameter was tested at values of 0.1, 0.01, and 0.001. As shown in Table 1, the dataset has an imbalanced class distribution, with an approximate 5:1 ratio between the largest and smallest classes. In addition to C and γ , the class weight parameter was set to “balanced”.

SKCV was used to split the dataset into training and testing sets. SKCV divides the data into k folds. One fold is used for testing, and the other $(k-1)$ folds are used to train the model for each iteration. This process is repeated k times, with each fold serving once as testing data (Prusty, Patnaik, & Dash, 2022). The value of k was set to 5.

Performance Evaluation

The performance of the proposed schizophrenia subtype classification model was evaluated using accuracy, precision, recall, and F1-score. Evaluation was performed using five-fold stratified cross-validation, and the reported results were calculated as the mean and standard deviation across the five folds. These evaluation metrics are derived from the confusion matrix and calculated from TP, TN, FP, and FN. For multiclass classification, macro-averaging was applied. The arithmetic mean of precision and recall for each class is used to find macro-average precision and macro-average recall. The harmonic mean of macro-precision and macro-recall is used to find the macro F1-score. The formulas used are defined in (5–10) (Haque, Islam, Tasneem, & Das, 2023):

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \quad (5)$$

$$\text{Precision}_K = \frac{TP_K}{TP_K + FP_K} \quad (6)$$

$$\text{Recall}_K = \frac{TP_K}{TP_K + FN_K} \quad (7)$$

$$\text{Macro-Precision} = \frac{\sum_{K=1}^K \text{Precision}_K}{K} \quad (8)$$

$$\text{Macro-Recall} = \frac{\sum_{K=1}^K \text{Recall}_K}{K} \quad (9)$$

$$\text{Macro F1-Score} = \frac{2(\text{MacroPrecision} \times \text{MacroRecall})}{\text{MacroPrecision} + \text{MacroRecall}} \quad (10)$$

where K is the number of classes, TP is the number of correct positive predictions, FP is the number of incorrect positive predictions, FN is the number of incorrect negative predictions, and TN is the number of correct negative predictions. The macro-average method assigns equal weight to each class, ensuring balanced evaluation across all classes. A high macro F1-score means that the predictions are distributed equally across all classes, whereas a low macro F1-score means that some classes are not predicted well. Therefore, the model with the highest macro F1-score was selected as the best-performing model. Accuracy, macro-precision, and macro-recall are also reported to provide a complete evaluation of overall performance.

RESULT

The dataset consisted of 218 medical records of patients diagnosed with schizophrenia. Clinical symptoms were processed using case-insensitive text matching according to 25 predefined symptom lists obtained from a psychiatrist. Each symptom was encoded into binary form, where 1 indicates symptom presence and 0 indicates its absence. These binary features were then used as input variables to classify four schizophrenia subtypes: paranoid, catatonic, undifferentiated, and residual.

Model evaluation was performed with five-fold stratified cross-validation. Performance was measured using accuracy, macro-precision, macro-recall, and macro F1-score. The reported results represent the mean and standard deviation across five folds. The evaluation was carried out sequentially, starting with a comparison of multiclass SVM approaches, followed by kernel functions and parameter configurations, to determine the most effective classification model. The performance comparison between the two multiclass SVM approaches, namely OAO and OAA, is presented in Table 5.

Table 5. Performance Comparison of OAO and OAA

Approach	Evaluation Metrics			
	Accuracy	Macro-Precision	Macro-Recall	Macro F1-Score
OAO	0.87 ± 0.05	0.90 ± 0.05	0.83 ± 0.11	0.85 ± 0.09
OAA	0.88 ± 0.05	0.92 ± 0.05	0.85 ± 0.08	0.87 ± 0.08

Table 5 shows that the OAA approach obtained better performance than OAO across all evaluation metrics. OAA obtained a macro F1-score of 0.87 and an accuracy of 0.87, while OAO achieved a macro F1-score of 0.85 and an accuracy of 0.88. The macro F1-score standard deviations were 0.08 for OAA and 0.09 for OAO. Based on these results, OAA was selected for further evaluation of the kernel and parameters.

Further analysis was performed to evaluate different kernel functions under the OAA approach to identify the most suitable kernel for schizophrenia subtype classification. The evaluated kernels included linear, polynomial, RBF, and sigmoid. The results are presented in Table 6.

Table 6. Performance Comparison of Kernel Functions (OAA)

Kernel	Evaluation Metrics			
	Accuracy	Macro-Precision	Macro-Recall	Macro F1-Score
Linear	0.87 ± 0.06	0.86 ± 0.11	0.83 ± 0.13	0.83 ± 0.13
Polynomial	0.87 ± 0.05	0.89 ± 0.10	0.83 ± 0.10	0.85 ± 0.10
RBF	0.88 ± 0.05	0.92 ± 0.05	0.85 ± 0.08	0.87 ± 0.08
Sigmoid	0.84 ± 0.08	0.83 ± 0.10	0.83 ± 0.10	0.82 ± 0.09

Table 6 shows that the RBF kernel achieved a higher macro F1-score of 0.87 among the evaluated kernels. The linear and polynomial kernels showed comparable accuracy of 0.87, but lower recall and F1-score than RBF. The sigmoid kernel obtained the lowest overall performance. Based on these results, the RBF kernel was used for further parameter configuration.

Further evaluation assessed the impact of various parameter configurations on the RBF kernel's performance. The regularization parameter (C) and gamma (γ) were varied to identify the optimal configuration. The results are presented in Table 7.

Table 7. Performance Comparison of Parameter Configurations (RBF – OAA)

Kernel	C	γ	Evaluation Metrics				
			Accuracy	Macro-Precision	Macro-Recall	Macro F1-Score	
RBF	0.1	0.1	0.85 ± 0.07	0.89 ± 0.06	0.85 ± 0.10	0.86 ± 0.09	
		0.01	0.49 ± 0.29	0.43 ± 0.26	0.48 ± 0.13	0.39 ± 0.21	
		0.001	0.49 ± 0.29	0.43 ± 0.26	0.48 ± 0.13	0.39 ± 0.21	
	1	0.1	0.87 ± 0.04	0.88 ± 0.04	0.84 ± 0.08	0.85 ± 0.06	
		0.01	0.83 ± 0.05	0.86 ± 0.07	0.83 ± 0.08	0.84 ± 0.08	
		0.001	0.30 ± 0.25	0.29 ± 0.32	0.44 ± 0.23	0.27 ± 0.27	
	10	0.1	0.89 ± 0.06	0.90 ± 0.08	0.86 ± 0.09	0.87 ± 0.09	
		0.01	0.87 ± 0.05	0.87 ± 0.07	0.85 ± 0.08	0.85 ± 0.07	
		0.001	0.1	0.83 ± 0.04	0.86 ± 0.07	0.83 ± 0.08	0.84 ± 0.07
			0.001	0.83 ± 0.04	0.86 ± 0.07	0.83 ± 0.08	0.84 ± 0.07

Table 7 shows that model performance varied across several parameter configurations. The highest macro F1-score of 0.87 was achieved at $C = 10$ and $\gamma = 0.1$. Configurations with $\gamma = 0.001$ resulted in significantly lower performance, as shown by a macro F1-score of 0.27. The configuration $C = 1$ and $\gamma = 0.1$ showed slightly lower variability across folds, yet achieved a lower macro F1-score compared to $C = 10$ and $\gamma = 0.1$. Based on these results, the configuration $C = 10$ and $\gamma = 0.1$ was selected as the final model configuration. The confusion matrix of this configuration is presented in Figure 2.

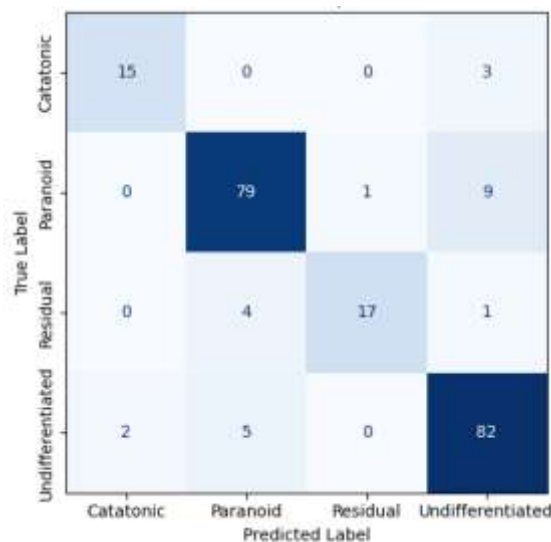


Figure 2. Confusion matrix of the RBF model for $C = 10$, $\gamma = 0.1$

Figure 2 presents the confusion matrix of the RBF model with $C = 10$ and $\gamma = 0.1$. The matrix illustrates the distribution of predicted and actual classes across the four subtypes of schizophrenia. Diagonal elements show instances that were correctly classified for each class, whereas off-diagonal elements show instances that were misclassified.

To further evaluate the effectiveness of the selected SVM model, its performance was compared with two baseline classifiers, namely Random Forest and Decision Tree. All models were trained and evaluated using the same binary symptom features, five-fold stratified cross-validation, and identical class imbalance handling. The SVM model used the previously selected optimal configuration, while the baseline models used fixed hyperparameter settings to ensure fair comparison. The results are presented in Table 8.

Table 8. Performance Comparison with Baseline Models

Model	Evaluation Metrics			
	Accuracy	Macro-Precision	Macro-Recall	Macro F1-Score
SVM RBF (OAA)	0.89 ± 0.06	0.90 ± 0.08	0.86 ± 0.09	0.87 ± 0.09
Random Forest	0.86 ± 0.05	0.87 ± 0.09	0.83 ± 0.10	0.84 ± 0.09
Decision Tree	0.75 ± 0.06	0.70 ± 0.08	0.78 ± 0.11	0.72 ± 0.09

Table 8 shows that the SVM RBF model got a higher macro F1-score of 0.87. Random Forest followed closely with 0.84, while Decision Tree achieved 0.72. For accuracy, SVM achieved 0.89, Random Forest 0.86, and Decision Tree 0.75.

DISCUSSIONS

The results demonstrate that the selection of a multiclass approach, kernel function, and parameter configuration plays an important role in classifying schizophrenia subtypes. The comparison of the multiclass approaches in Table 5 shows that OAA achieved a higher macro F1-score of 0.87 than OAO. In addition, OAA's macro F1-score standard deviation was slightly lower at 0.08, suggesting more stable performance across folds. Similar results have been reported in prior multiclass SVM studies, indicating that OAA achieved better performance than OAO (Delimayanti, Sari, Laya, Faisal, & Pahrul, 2021). Other research, however, has demonstrated that OAO can achieve comparable performance, although it requires training multiple binary classifiers, which increases computational complexity (Krebs, Bagui, Mink, & Bagui, 2024).

Kernel evaluation further demonstrated that the RBF kernel achieved a higher macro F1-score of 0.87, outperforming the linear, polynomial, and sigmoid kernels, which achieved 0.83, 0.85, and 0.82, respectively. The linear kernel showed competitive performance, but the higher result achieved by RBF indicates that the relationships among schizophrenia classes may involve non-linear patterns. Similar findings have been reported in prior disease classification studies, where RBF achieved better performance than other kernel functions (Aurelia, Rustam, Wirasati, Hartini, & Saragih, 2021).

Further analysis of parameter configurations in Table 7 shows that both C and γ influenced model performance. A low gamma value of 0.001 resulted in a lower macro F1-score of 0.27. In RBF, gamma determines how far the influence of each training data point extends. Lower gamma values indicate that each data point has a large area of influence, which may lead to underfitting. Increasing C improves performance by assigning a higher penalty on misclassification, but may increase the risk of overfitting. The highest macro F1-score of 0.87 was obtained at $C = 10$ and $\gamma = 0.1$. This signifies that choosing appropriate parameter values is essential for optimal model performance.

The confusion matrix in Figure 2 provides more detail on per-class performance for the configuration $C = 10$ and $\gamma = 0.1$. The model correctly classified 15 of 18 catatonic cases, 79 of 89 paranoid cases, 17 of 22 residual cases, and 82 of 89 undifferentiated cases. Misclassifications were most frequent between paranoid and undifferentiated, with 9 paranoid cases predicted as undifferentiated and 5 undifferentiated cases predicted as paranoid. In the residual class, 4 cases were misclassified as paranoid and 1 as undifferentiated, while 3 catatonic cases were misclassified as undifferentiated. The higher performance in paranoid and undifferentiated may be owed to their larger sample size. The model shows stable performance across classes, although certain classes still pose challenges for differentiation.

Comparison with baseline models in Table 8 demonstrates that SVM RBF constantly obtained higher performance across evaluation metrics. SVM RBF obtained a macro F1-score of 0.87 and an accuracy of 0.89, outperforming Random Forest and Decision Tree. Although Random Forest showed competitive and stable performance, its macro F1-score of 0.84 was lower than SVM RBF. Decision Tree obtained the lowest overall performance. These results were obtained under the same experimental settings, ensuring fair comparison within the dataset.

The proposed model achieved a macro F1-score of 0.87 and an accuracy of 0.89 using five-fold stratified cross-validation. By contrast, earlier research on schizophrenia subtype classification using FKNN with 300 medical data and 10-fold cross-validation reported a macro F1-score of 0.94 and an accuracy of 0.94 (Prambudi et al., 2025). Another study on thyroid disease classification utilizing medical data evaluated multiple machine learning algorithms using five-fold stratified cross-validation with hyperparameter optimization, reporting an SVM F1-score of 0.97 (Elbillihy, Abdelhalim, Ashour, & Nafea, 2026). Despite the performance reported in the present study being lower, it is important to consider variations in dataset characteristics, class distribution, clinical context, and validation methods, as these factors limit direct comparisons of performance outcomes across studies.

From a clinical perspective, misclassification between subtypes can affect how a patient's symptoms are interpreted and recorded. These subtypes present with similar symptoms, but correct classification is important for determining the appropriate focus of care and long-term monitoring. Therefore, the proposed model should not

replace a psychiatrist's diagnosis. It can be used as a screening or decision-support tool to provide a second opinion and help physicians identify possible subtype patterns, but the final decision must remain with psychiatrists.

Several limitations should be acknowledged. The dataset was collected only from a single hospital, which may limit its generalizability to other clinical settings. Subtype labels depend on the accuracy and completeness of medical records, and variability among physicians may affect model performance. In addition, the classification of schizophrenia subtypes has been debated, especially since DSM-5 and ICD-11 no longer officially recognize subtype categories. This could affect the long-term clinical usefulness of subtype-based machine learning models.

CONCLUSION

This study demonstrated that a multiclass SVM model can classify schizophrenia subtypes using clinical symptom records, achieving a macro F1-score of 0.87 and an accuracy of 0.89 with five-fold stratified cross-validation. The findings emphasize that choosing the right multiclass approach, kernel function, and parameter configuration significantly influences classification performance, with the OAA approach and RBF kernel yielding the most stable results. Clinically, the model could assist in identifying subtypes through a systematic assessment of symptom patterns. Although it is not intended to replace psychiatric diagnosis, it can serve as a screening or decision-support tool to improve consistency in subtype evaluation. However, the dataset was obtained only from a single hospital and relies on documented clinical records, which may limit its generalizability. In addition, schizophrenia subtype classification remains debated in current diagnostic frameworks like DSM-5 and ICD-11. Future research should use more diverse datasets and consider other diagnostic approaches to improve robustness and clinical applicability.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to RSJD Atma Husada Mahakam Samarinda for providing access to the medical record data that was used in this study. The institution's help and cooperation were very important to the successful completion of this research.

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