Towards Enhanced Infant Care: Tuna-Inspired Backing Vector Machine for Cry Identification

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Promptly and precisely recognizing signs of discomfort in new-borns, such as cries is vital in infant care and essential to ensure the child's well-being. Even though baby cry analysis has advanced, many current techniques need help with precision and dependability, which could cause babies' distress signals to be misinterpreted. This work suggests a novel tuna-inspired backing vector machine (TI-BVM) to solve the requirement for a better cry recognition system. The suggested TI-BVM uses cutting-edge signal processing methods to identify minute differences in baby cries, taking inspiration from tuna fish's complex audio processing abilities. Many cry sample datasets are used to train the model, considering variables including modulation of frequencies, time frame, and pitch. The zero crossing rate methodology is used to extract the characteristics from the dataset. This study uses the Python platform to investigate the recognition of baby cries using TI-BVM. Additionally, the performance of the suggested way is examined and contrasted with alternative approaches. The work's outcomes demonstrate the proposed method classifies various cry kinds. Additionally, this study indicates that the suggested TI-BVM has potential as a novel tool for improving baby care by identifying cries.

Keywords: Infant Care, Cry, Signal Processing, Tuna-Inspired Backing Vector Machine (TI-

BVM).

1. Introduction

Taking care of a baby is a very fulfilling and transforming experience that brings about a great deal of pleasure, but it also requires a significant commitment from those who provide the care. Taking care of a baby is much more than simply meeting their basic requirements, which include food, clean diapers, and a safe space to sleep. It includes a universal strategy for rising a child's early months of physical, emotional, and cognitive development. The ability of cry identification is essential to the process because it enables parents and other caregivers to understand the distinct language that a new-born uses to communicate [1, 2].

Taking care of an infant requires balancing their current demands with their long-term wellbeing. Babies are totally reliant on their caretakers for protection, comfort, and nourishment throughout the first few months of life. Since parents or other main caregivers, it becomes critical to comprehend the subtleties of new-born communication, since crying is the primary mode of expression. Identifying the different kinds of cries and knowing how to react to them is an essential part of caring for a new-born [3].

A new-born uses crying as their main form of communication to express their wants and to show that they are uncomfortable or distressed and it takes a comprehensive awareness of the many tones, pitches, and patterns that distinguish each scream to decipher its meaning. Infants often scream because of exhaustion, hunger, and discomfort, but they may also cry out of loneliness, overstimulation, or even pain. Caregivers may provide a responsive and loving atmosphere that promotes trust and emotional stability by aware of these minor variances [4, 5].

Making the distinction between screams that signify regular requirements and those indicate a serious problem is one of the main obstacles in providing care for infants. The subject of new-born cry analysis has advanced to the point that tools and technology have been developed to help parents and caregivers with this process. To assist caretakers, recognize certain indicators and react appropriately, machine learning (ML) algorithms, for example, it has been used to evaluate and classify various cry patterns. This use of technology in baby care not only improves the caregiver's capacity to respond to the child's needs but also advances our knowledge of how babies communicate [6, 7].

Apart from learning to identify cries, there are many additional aspects of holistic baby care. The establishment of a stable and protective routine, the encouragement of healthy sleeping practices, responsive and interactive play, and the formation of a safe bond between the caregiver and the new-born are all essential to the child's general development. Furthermore, caregivers may adjust their interactions to promote the infant's developing skills by being aware of developmental milestones that correspond with the infant's age [8, 9].

The foundation of a child's early experiences, affecting their physical, emotional, and cognitive development, is laid by new-born care and cry recognition. Combining technology innovations with a responsive, compassionate parenting strategy enables parents and other caregivers to understand the complex language of an infant's screams. Caregivers may provide the groundwork for the newest members of communities to have a healthy, safe, and prosperous future by adopting this multidimensional approach to baby care [10].

The aim of this research is to improve the accuracy and performance of cry recognition, using tuna swam optimization and backing vector machine. We will discuss the related works in - Section 2. The proposed methods are shown in Section 3. The experimental results are discussed in Section 4. And the last section of this paper is the conclusion in - section 5.

2. Related works

The article [11] used a deep neural network (DNN) classifier to recognized infant cry emotions. Based on many criteria, infant cries were classified as hunger, sleep, or discomfort. The proposed approach engaged quick-calming methods like music or parental speech. The results were promising, demonstrating the efficacy of the DNN-based system in recognizing infant cry emotions. Research [12] investigated behavioural solutions for newborn sleep issues, with a particular emphasis on the impact of parent’s ability to tolerate their crying and their thoughts about sleep. They looked at how these elements fit into treating and comprehending newborn sleep issues. The results enhanced our knowledge of practical methods for controlling and enhancing newborn sleep. According to the author of, [13] examined the use of cry detection in academic environments, including neonatal intensive care units (NICU). They presented a deep neural network (DNN) based cry detection approach and investigated the possibility of using a well-designed synthetic dataset in place of field data for training. The acoustic scene simulation technique may trained a cry detection system with good results, since they had the highest Area Under Precision-Recall Curve (PRC-AUC).The author, [14] utilized machine learning method to evaluated cry-translator activity by described the sound of an infant's cry. In order to use cry-translation techniques for the analysis of colic cries under the assumption of pain. They used these algorithm to predicted colic baby behaviour. Cries from fussiness, hunger, fussiness or pain were identified with accuracy used the cry-translation algorithm.

The suggested two-step method for automated newborn cry detection used continuous audio inputs. A volume-based thresholding approach removed background noise, then convolutional neural network (CNN) models recognized newborn cries [15]. CNNs can reliably categorized and detected newborn cries, promising to improved parental response and infant health. Research [16] presented preliminary results on the automatic mother language identification of around 7,500 cry units from full-term, healthy babies with French, Arabic, and Italian mother tongues. The BioVoice software program computed acoustic data and twelve distinct melodic forms. Random Forest and four neuro-fuzzy classifiers were used to classify cry identification. A long-range infant monitoring and regulating system was created in the paper [17]. The system was comprised of hardware architecture that was interconnected with an Internet of Things (IoT) network to monitored the baby's status in real time, including crying, waking, and cleanliness, as well as its surroundings, including temperature, humidity, and motion. A working prototype has been developed based on the study's conclusions. It collects monitoring data and uses a mobile application to distributed and showed it directly to customers.

To examined how adult men found both male and female newborn screams unpleasant [18]. A psychological technique was used to test adult men's responses to infant cries, and depending on baby's gender was crying, significant variations in the reported feelings of dislike were observed. Author [19] proposed classifying baby screams into three categories: those were caused by food, sleep, and pain. For each crying structure, audio feature engineering found twelve features in the frequency and time domains. Random forests were used to pick the most useful features. The results of these studies showed that the grouped-support-vector network powered by extreme gradient boost was able to identify Infants often cry out with a high degree of accuracy. The convolutional neural network (CNN) and long short-term memory (LSTM) are two examples of deep learning (DL) algorithms that were employed in the paper [20] to identify basic requirements in newborns, including hunger and thirst, the need for a diaper change, emotional needs, and discomfort from medical treatments. These findings could serve as standard for further programs designed to educate parents on the health and requirements of their newborns.

3. Methodology

The article presents a tuna-inspired backing vector machine (TI-BVM) for newborn scream identification. The TI-BVM identifies cries by modulation, time frame, and pitch using advanced signal processing and cry datasets, showing its potential to improve newborn care.

3.1 Data set

The dataset is sorted as the initial step. For this approach, we considered certain portions of the datasets. Sound recordings of children crying have been set together in a file called give-a-cry-corpus. The recordings were made by discourse research groups. This dataset contains audio clips of multiple newborn infants who were captured in various kinds of circumstances. There are eight different sound record configurations in this dataset: awake, bellied, burping, uncomfortable, hugged, hungry, sleepy, and tired.

3.2 Feature Extraction Using Zero Crossings Rate

Zero Crossings Rate provides a quantitative evaluation of vocalization patterns for better understanding and response, making it a useful parameter in baby care, especially in cry recognition. A zero crossing phenomenon arises in the framework of discrete-time signals when successive samples exhibit distinct algebraic signs. A signal's frequency content can be determined by counting the number of zero crossings per transmission. The number of times the voice signal's amplitude passes through zero in a specific time interval or frame is known as the zero-crossing rate. The average zero-crossing rate is much less accurate when figuring out voice signals since they are broadband signals. However, a representation based on the short-time average zero-crossing rate may provide approximations of spectral features.

The following is an illustration of zero crossing rate in Equations (1-3):

$$Z_m = \sum_{n=-\infty}^{\infty} |\, \mathrm{sgm}[y(n)] - \mathrm{sgm}[y(n-1)]| v(m-n) \qquad (1)$$

Where

$$\mathrm{sgm}[y(m)] = \begin{cases} 1, y(m) \geq 0 \\ -1, y(m) < 0 \end{cases} \quad (2)$$

And

$$v(m) = \begin{cases} \frac{1}{2M} \text{ for}, 0 \leq m \leq M-1 \\ 0 \text{ for, otherwise} \end{cases} \quad (3)$$

The speech production model states that unvoiced speech has greater energy at higher frequencies, but voiced speech has more energy below 3 kHz because of the glottal wave's spectrum fall. The zero crossing rate and energy distribution exhibit significant frequency dependence, according to which zero crossing rates are higher at higher frequencies and lower at lower frequencies. In the speech signal, there is no voice when the zero-crossing rate is high; there is a voice when it is low in Equation (4).

$$E_m = \sum_{m=-\infty}^{\infty} [y(n)v(m-n)]^2 \quad (4)$$

The short-time energy representation's characteristics depend on the window selection. The Hamming window was employed in our model. Compared to a similar rectangular window, the hamming window provides more absorption beyond the band pass.

3.3 Tuna-Inspired Backing Vector Machine for Cry Identification (TI-BVM)

The Tuna-Inspired Backing Vector Machine for Cry Identification is a cutting-edge ML technique designed to recognize and categorize baby screams. It is impacted by the behaviour of tuna fish. This new strategy is based on tuna fish's incredible ability to distinguish diverse underwater sounds and adapt to their environment. The Tuna-Inspired Backing Vector Machine seeks to improve newborn care and well-being by emulating this natural process by improving infant cry recognition's precision and efficacy.

3.3.1 Tuna Swam Optimization

The Tuna Optimization Algorithm improves automated childcare systems by providing effective care for infants and identifying cry patterns. The tuna swarm uses parabolic and spiral foraging, two efficient predatory techniques. When the swarm of tuna uses the symbolic feeding technique, every fish follows the one in front of it. To surround the victim, the tuna swarm forms a parabola. A tuna swarm will create spiral patterns and drive its prey towards areas of shallow water when it employs the spiral foraging strategy. Mark has a higher chance of being caught. Observing these two foraging patterns of tuna swarms, researchers proposed a new swarm intelligence optimizer called Tuna Swam Optimization (TSO).

3.3.1.1 Population Startup

A tuna swarm contains Number of Participants (NP), which represents the parameter indicating the number of individuals or entities within the tuna swarm. In the first phase of the swarm, the tuna swarm optimisation algorithm produces the first swarm in the search space at random.

The following mathematical formulas can be used to initialize tuna individuals in Equation (5):

$$y_i^{int} = rand.(ub - lb) + lb = \left[y_i^1, y_i^2, \ldots, y_i^j\right]$$

$$\begin{cases} i = 1, 2, \ldots, NP \\ j = 1, 2, \ldots, Dim \end{cases} \quad (5)$$

Assuming that y_i^{int}The rand is a random variable with a uniform distribution that ranges from 0 to 1, and the i^{th}tuna, ub, and lb stand for the upper and lower bounds of the tuna exploration range, respectively. Specifically, every individual in the tuna swarm provides a possible TSO solution. Each tuna is composed of a series of Dim-dimensional numbers.

3.3.1.2 Parabolic Foraging Method

The variables ub and lb represent the maximum and minimum boundaries of the tuna's exploration range. Consider X as a random variable that conforms to a uniform distribution ranging from 0 to 1. Additionally, let y_i^{int} be the i^{th} tuna. Each individual inside the tuna swarm, represented as y_i^{int} corresponds to a potential solution within the Tuna Swam Optimization (TSO).

Each and every tuna is composed of a set of little integers are shown in Equations (6-7).

$$y_i^{t+1} = y\begin{Bmatrix} y_{best}^t + rand.\left(y_{best}^t - y_i^t\right) + TF.p^2\left(y_{best}^t - y_i^t\right), \text{if rand} < 05, \\ TF.p^2.x_i^t \qquad \text{if rand} < 05 \end{Bmatrix} \quad (6)$$

$$p = (1 - \frac{t}{t_{max}})^{\frac{t}{t_{max}}} \quad (7)$$

Where t is the current iteration, t_{max}denotes the maximum number of iterations present, and TF is a random integer of 1 or 1.

3.3.1.3 The spinning process Forage

Parabolic and spiral foraging are excellent cooperative foraging methods. A few tuna can lead the swarm while hunting prey, but most fail. Tuna will follow a small group of fish after their meal. To catch prey, the tuna swarm will create a spiral. Spiral foraging tuna swarms interact with each other, the finest foragers, and their associates. Even the most skilled individual may have difficulties in guiding the swarm towards their target. The tuna will decide at random in Equation (8).

$$y_i^{t+1} = \begin{cases} \propto_1.\left(y_{rand}^t.\pi.\left|y_{rand}^t - y_i^t\right| + \propto_1.y_i^t\right) \\ \propto_1.\left(y_{rand}^t.\pi.\left|y_{rand}^t - y_i^t\right| + \propto_1.y_{i-1}^t\right), \\ \qquad i = 1, 2, \ldots, NP \\ \propto_1.\left(y_{best}^t.\pi.\left|y_{best}^t - y_i^t\right| + \propto_1.y_i^t\right), \quad , \text{if rand} < \frac{t}{t_m} \\ \qquad i = 1 \\ \propto_1.\left(y_{best}^t.\pi.\left|y_{best}^t - y_i^t\right| + \propto_1.y_i^t\right), \\ \qquad i = 1, 2, \ldots, NP \end{cases} \quad (8)$$

Hence, in the $t + 1$ iteration, y_i^{t+1} represents the ith tuna. $y_{\text{the best}}^t$ is the greatest person.$y_{rand}^t$is the reference point that was randomly selected from the tuna swarm. The value of the coefficient of trend weight, or $\alpha 1$, is used to guide the tuna individual as it swims toward the ideal individual or toward randomly chosen nearby individuals. A tuna's path towards the person in front of it is determined by the trend weight coefficient, or α2. The distance between the optimum individual or randomly chosen reference individual and the actual individual is controlled by the distance parameter, π. Their mathematical calculation model is follows in Equations (9-12):

$$\propto_1 = a + (1 - a).\frac{t}{t_{max}} \tag{9}$$

$$\propto_1 = (1 - a) - (1 - a).\frac{t}{t_{max}} \tag{10}$$

$$\pi = e^{bl}.\cos 2(\pi b) \tag{11}$$

$$l = e^{3\cos((\left(t_{max} + \frac{1}{t}\right) - 1)\pi)} \tag{12}$$

The constant ais used to quantify the level of tuna tracking, whereas b is a uniformly distributed random variable within a certain period.

3.3.2 Backing Vector Machine

The Backing Vector Machine uses support vector machine techniques to identify and analyse infant cries acoustic features for automated cry analysis in infant care. Backing vector machines (BVM) are very suitable for addressing nonlinear classification issues by using the kernel method, as clarified in the present paper.

One can find a hyperplane $f(x) = 0$ for linearly separable data as follows in Equation (13):

$$f(x) = v^T x + b = \sum_{j=1}^{n} v_j x_j + b = 0 \tag{13}$$

where v is an n-dimensional vector and b is a scalar field that finds the optimal separation hyper-plane leaving the most margin from both classes. In situations involving nonlinear classification, the kernel technique is used. In order to formulate the potential of achieving linear separation, the kernel technique converts the data into a higher dimensional feature space. In VM, data is transformed from the input space to a feature space using a nonlinear kernel function. In this space, the discriminant function is in Equation (14):

$$f(x) = v^T(x) + b \tag{14}$$

The nonlinear BVM produces linear classification via the process of training the BVM for the mapped features (x), which comes after mapping the input data x completely into the feature space. The training instances are combined to form the weight vector ($w = \sum_{i=1}^{n} a_i x_i$), Equations (15-16) has the following form:

$$v = \sum_{i=1}^{n} a_i x_i \tag{15}$$

This phrase takes form in the feature space:

$$f(x) = \sum_{i=1}^{n} a_i K(x_i x_j) + b \tag{16}$$

The associated kernel$K(x_i x_j)$ may be used to train nonlinear BVMs by substituting the inner products in Equation (17).

$$K(x_i x_j) = (x_i)^T x_j \tag{17}$$

Then, using the kernel function as a reference, the nonlinear BVM's resulting classifier is represented by Equaiton (18):

$$f(x) = \sum_{i=1}^{n} a_i \, K(x_i x_j) + b \tag{18}$$

Several BVM-based tool wear classification and evaluation methods have been reported in the area of tool condition monitoring. In order to predict the tool state of a coated abrasive-compliant belt during the machining process, this research makes use of smart sensors.

The use of Tuna Swarm Optimisation (TSO) for feature selection and Backing Vector Machine for cry detection is utilized in newborn care. The performance of Backing Vector Machines is enhanced by using TSO to optimize subsets of features. The BVM, trained using annotated data, accurately identifies the cause of an infant's scream distinguishing between hunger and discomfort. This approach combines the TSO optimization abilities and BVM classification abilities to provide a robust solution for precise cry detection in newborn care applications. Algorithm 1 shows a tuna-inspired backing vector machine (TI-BVM).

Algorithm 1:Process of TI-BVM

```
import numpy as np
from sklearn import svm
tso_parameters = {
'population_size': 50,
'max_iterations': 100,
svm_parameters = {
'kernel': 'linear,'
}
def objective_function(features):
svm_model = svm.SVC(**svm_parameters)
tso_swarm = initialize_tso_swarm(**tso_parameters)
for iteration in range(tso_parameters['max_iterations']):
tso_swarm = update_tso_swarm(tso_swarm)
For a particle in tso_swarm:
particle.fitness = objective_function(particle.position)
best_particle = get_best_particle(tso_swarm)
selected_features = best_particle.position
final_svm_model = svm.SVC(**svm_parameters)
```

4. Experimental results

Python programming was used, along with packages like scikit-learn. A PC with an Intel Core i7 CPU, 16GB RAM, and Python 3.8 was used to test the system. The proposed approach was compared with existing methods like K-Nearest Neighbours (K-NN), Support Vector Machine (SVM) and Random Forest (RF) [21] with this parameters Accuracy, precision, recall, and F1 score.

4.1 Accuracy

The accuracy refers to the efficacy of a system or model in accurately categorizing and identifying distinct sorts of newborn cries. A greater accuracy signifies a dependable and accurate system for identifying and reacting to newborn distress signals, leading to enhanced caring and overall well-being. The accuracy may be estimated using the Equation (19):

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{False Positives} + \text{True Negative} + \text{False Negatives}} \tag{19}$$

Where

- The number of times the model properly recognizes a cry is True Positives (TP).
- The number of times the model misidentifies a cry is False Positives (FP).
- The amount of times the model misses a certain cry is False Negatives (FN).
- The number of times the model properly recognizes no cry is True Negatives (TN)

Figure 1 and Table 1 illustrate the accuracy result. When comparing our proposed method (TI-BVM -98.95%) with the existing method (K-NN-98.88%, SVM-98.6%, and RF-98.33%). Our proposed method is greater than the existing and it shows that our model is superior in cry recognition system.

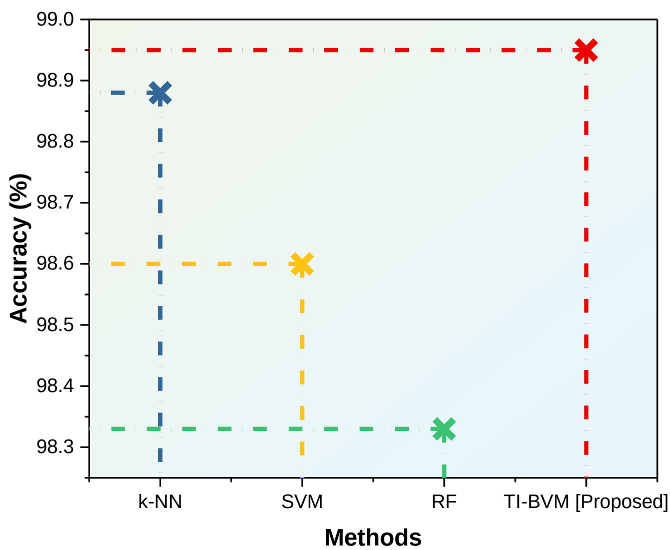

Figure 1: Outcome of accuracy

Table 1: Value of accuracy

Methods	Accuracy (%)
K-NN[21]	98.88
SVM[21]	98.6
RF[21]	98.33
TI-BVM[proposed]	98.95

4.2 Recall

The recall is a performance metric that assesses a system's ability to identify instances of a specific class among all the cases of class in the dataset. The recall is especially crucial when the cost of missing a positive occurrence (false negative) is large. Infant care and cry identification Recall can be calculated using this Equation (20):

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \qquad (20)$$

Figure 2 and Table 2 illustrate the recall result. When comparing our proposed method (TI-BVM -98.97%) with the existing method (K-NN-98.88%, RNN-98.6%, and SVM-98.33%). Our proposed method is greater than the existing and it shows that our model is superior in cry recognition system.

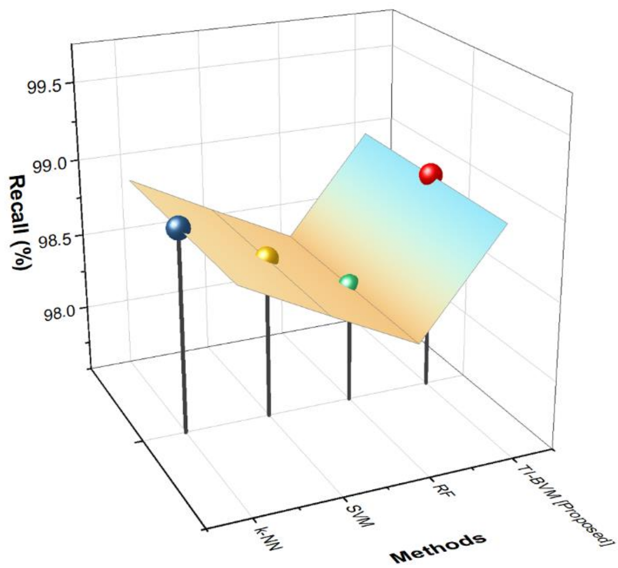

Figure 2: Outcome of recall

Table 2: Value of recall

Methods	Recall (%)
K-NN[21]	98.88
SVM[21]	98.6
RF[21]	98.33
TI-BVM[proposed]	98.97

4.3 Precisions

Precision is used in classification tasks like infant cry identification. Classifier precision is the ratio of true positives prediction to total positive predictions. Infant care and cry identification precision can be calculated using this Equation (21):

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives+False Positives}} \tag{21}$$

Figure 3 and Table 3 illustrate the precision result. When comparing our proposed method (TI-BVM -98.98%) with the existing method (K-NN-98.89%, RNN-79.6%, and SVM-98.6%). Our proposed method is greater than the existing and it shows that our model is superior in cry recognition system.

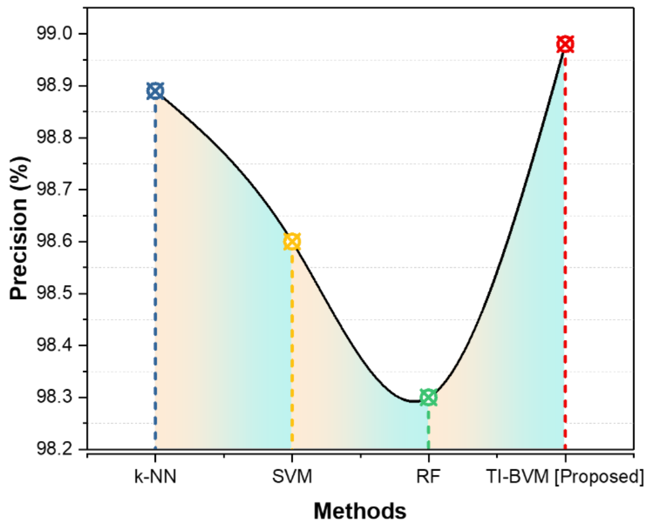

Figure 3: Outcome of precision

Table 3: Value of Precision

Methods	Precision (%)
K-NN[21]	98.89
SVM[21]	98.6
RF[21]	98.3
TI-BVM[proposed]	98.98

4.4 F1 score

The F1 score is a statistic used to evaluate the effectiveness of a classification model in baby care and cry identification. It combines precision and recall into a single rating, resulting in more balanced evaluation of model's correctness.

The F1score is Equation (22) as follows:

$$\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision + Recall}} \tag{22}$$

Figure 4 and Table 4 illustrate the F1 score result. When comparing our proposed method (TI-

BVM -99.02%) with the existing method (K-NN-98.88%, RNN-98.6%, and SVM-98.33%). Our proposed method is greater than the existing and it shows that our model is superior in cry recognition system.

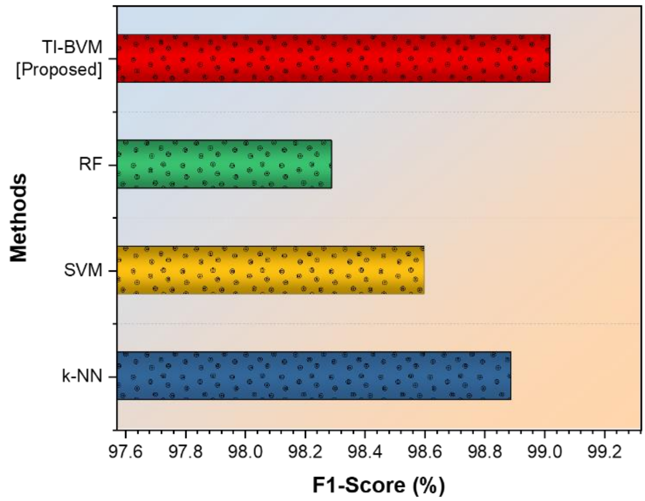

Figure 4: Outcome of F1score

Table 4: Value of F1 score

Methods	F1 score (%)
KNN [21]	98.89
SVM[21]	98.6
RF[21]	98.29
TI-BVM[proposed]	99.02

5. Conclusion

The prompt highlights the important of identifying symptoms of anxiety in babies as soon as possible, especially their screams, to protect their general wellbeing. Although techniques for interpreting infant screams have advanced, more accuracy and dependability are needed. This work presents an innovative approach that uses advanced signal processing methods inspired by the intricate audio processing abilities of tuna fish: the tuna-inspired backing vector machine (TI-BVM). The TI-BVM is trained on a variety of cry datasets, taking into consideration variables like pitch, time interval, and frequency modulation, and using the zero crossing rate approach for feature extraction. The research, which was carried out on the Python platform, demonstrates the level that the TI-BVM can classify various types of cries. The outcomes show that the suggested strategy outperforms traditional approaches and delivers superior recognition accuracy, precision, recall, and F1 scores of 98.95%, 98.98%, 98.97%, and 99.02% respectively. The promising findings indicate that this novel approach may be a useful instrument for improving baby care by recognizing and interpreting screams, hence resolving the shortcomings of existing methods. The limitation is limited real-world testing. The future scope of this project includes integration with smart devices, real-time monitoring, and enhanced cry variability analysis.

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