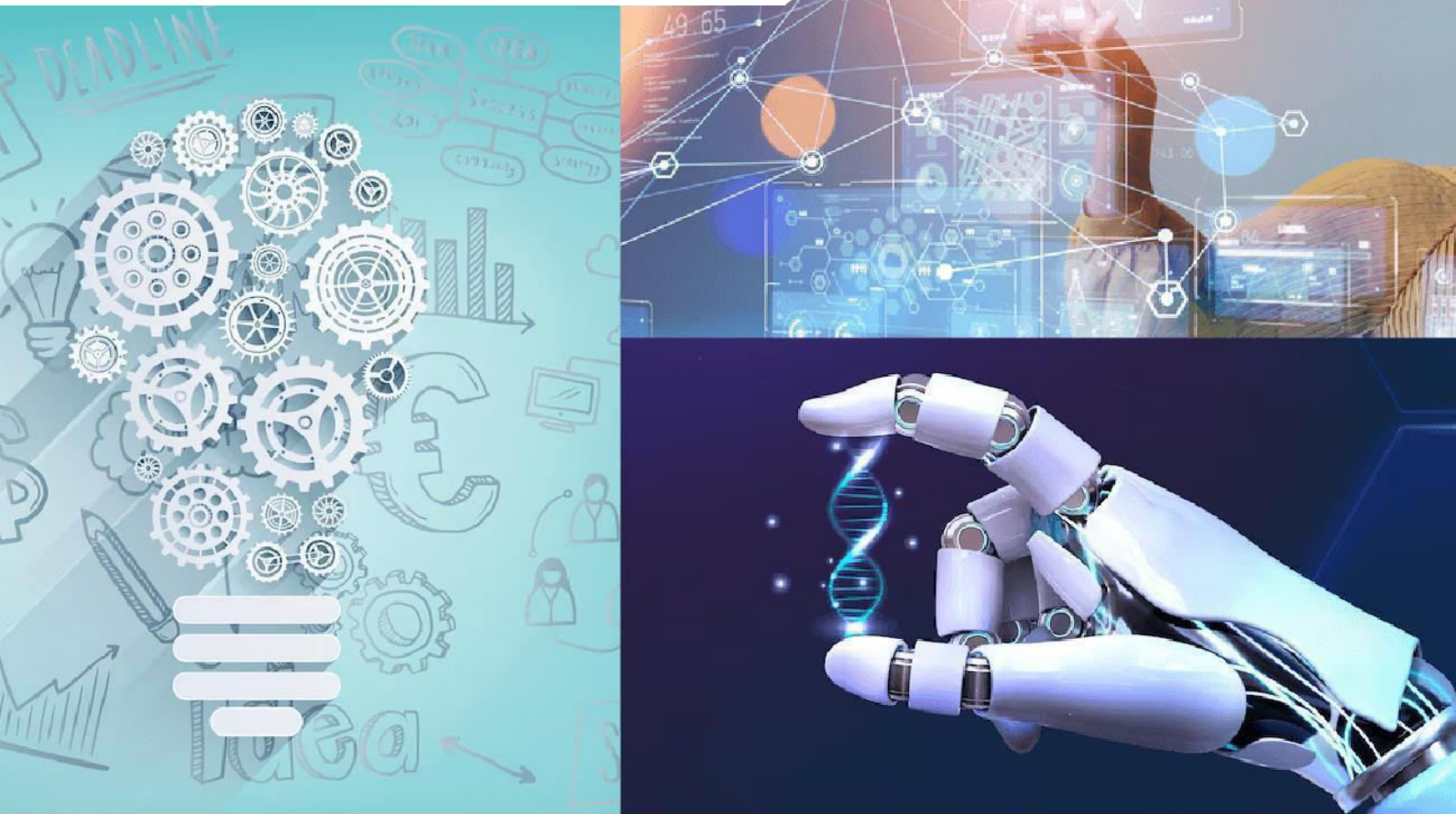




International Journal of Advanced Research in Education and Technology (IJARETY)

Volume 13, Issue 3, May - June 2026

Impact Factor: 9.971



Binary Patterns Pyramid Filter-Based Feature Extraction with Machine Learning Classifiers for Automated Detection of Down Syndrome using the MultiStudy Research Hub Dataset

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ABSTRACT: The most common chromosomal disorder worldwide is Down syndrome (DS) which occurs in 1 in 700 live births. Prompt diagnosis of DS is critical in order to initiate timely interventions that can optimize cognitive, physical and social outcomes. Although the clinical diagnostics have come a long way, there is a lack of study in the DS detection literature of an automated image-based classification system that is computational efficient and interpretable. In this paper, the efficiency of the Binary Patterns Pyramid Filter (BPPF) as a feature extraction technique for the classification of Down syndrome images using six machine learning classifiers of NaiveBayesUpdateable, SGDText, Bagging, Stacking, REPTree and Locally Weighted Learning (LWL) which are implemented under Weka environment is assessed. The Down Syndrome MultiStudy Research Hub dataset, which consists of 6,078 balanced images, was split into training (4,200), validation (1,798), and testing (80) sets and sourced from Kaggle. The extracted binary texture pattern features were multi-scale descriptors provided by the BPPF. The extracted feature vectors were independently tested with six classifiers, and the performance of these classifiers was assessed based on accuracy, precision, recall, ROC area, PRC area and training time. BPPF+Bagging had the best overall performance with an accuracy of 90.50%, a precision of 0.91, the recall of 0.91, ROC area of 0.94, and PRC area of 0.94, taking 2.19 seconds to train. BPPF+SGDText achieved the second best accuracy (87.61%) and took the least training time (1.15s). With the highest training cost (3.08s) BPPF+Stacking had the lowest accuracy (82.50%). The ensemble Bagging and the PWF are an effective, reliable, and efficient framework for automatic classification of Down syndrome images. The results support the use of BPPF as a competitive and interpretable texture feature descriptor for genetic disorder image analysis, in comparison to the deep learning methods. This research involves deconvolution (down syndrome deconvolution) of the image features extracted from the genetics disorder image to detect the presence of the genetic disorder using machine learning technique, specifically bagging and binary patterns pyramid filter, with the purpose of being useful in the computer-aided diagnosis field.

KEYWORDS: Down Syndrome, Trisomy 21, Binary Patterns Pyramid Filter, Machine Learning, Bagging, Image Classification, Weka, Genetic Disorder Detection, Texture Feature Extraction, Computer-Aided Diagnosis..

I. INTRODUCTION

Trisomy 21, also known as Down syndrome (DS), is a condition in which there is a complete or partial third chromosome 21. It is the most frequent autosomal chromosome abnormality that is live compatible and occurs in about 1 per 700 live births worldwide [1]. The phenotype can range from typical features such as "Almond eyes," flat nasal bridge, and tongue protrusion, to intellectual disability, congenital heart abnormalities, and other thyroid disorders, respiratory infections, and early onset Alzheimer's disease [2]. Although the clinical spectrum of DS is heterogeneous,

there are characteristic physical features that allow it to be addressed with automated image based detection methods. The diagnosis of DS is traditionally made on cytogenetic karyotyping or prenatal genetic testing, both of which are definitive, but are expensive, time consuming and require specialty laboratory infrastructure. With the development of machine learning and deep learning approaches in the field, computer-aided diagnosis (CAD) systems show great promise for fast and scalable low-cost DS screening, especially in low-resource healthcare environments [3]. Early identification is especially important as early intervention, including speech, physiologic, and occupational therapies, and inclusive education, has been shown to have a significant impact on developmental outcomes and quality of life of individuals with DS [4]. Most of the classic machine learning pipelines involve image-based feature extraction methods for medical image classification. The Binary Patterns Pyramid Filter (BPPF) is a multi-scale texture feature descriptor which hierarchically encodes the distribution of local binary patterns in spatial resolution levels, reflecting fine-grained and coarse structure information in texture [5]. BPPF is ideally suited for encoding the spatial distribution of morphological features, such as periorbital areas, nasal outlines, and patterns of facial symmetry, all of which are different in DS than in typically developing individuals in the context of DS facial image analysis.

In this work, BPPF is used as a feature extraction algorithm and six machine learning classifiers are used: NaiveBayesUpdateable, SGDText, Bagging, Stacking, REPTree and Locally Weighted Learning (LWL). Kaggle's Down Syndrome MultiStudy Research Hub dataset [16] is used. The purpose of the study is to find an optimum combination of the classifiers in BPPF class to achieve an automatic binary DS classification and to provide a reproducible Bppf baseline for DS detection based on handcrafted features.

Paper is organized as follows. Section II describes related works. The flow diagram represents the step of the algorithm. Materials and methods given in Section III. Section IV presents experimental results showing results of images tested. Finally, Section V presents conclusion.

II. RELATED WORK

Trisomy 21 is the commonest chromosomal abnormality associated with postnatal survival, affecting 1 in 700 live births worldwide, and is known as down syndrome (DS). Clinical forms of DS are quite different in different populations. In their cross-population study, Kruszka et al. [1] studied DS in a wide range of ethnic and geographical groups and found that, although the chromosomal basis of DS is the same across all populations, facial gestalt and clinical features have significant population-specific variability.

Neurocognitive profile of trisomy 21: intellectual disability, language delay, memory loss, visuospatial deficits, wide range of severity. Jafri and Harman [2] have performed a thorough review of neurocognitive abilities in DS children, including cognitive outcome variability throughout the lifespan and the importance of early childhood to target intervention that best shapes developmental trajectories. Although the positive outcomes of early diagnosis of DS and early start on support services are well known, a clinical problem is a delay in the diagnosis and the beginning of support services for DS. Fredes et al. [3] studied a population of children with DS and concluded that a significant number of children started structured therapeutic programs significantly later than the recommendations for evidence-based intervention. Prenatal screening for DS has been a main area of application of machine learning, especially for the second trimester biochemical marker-based and ultrasonographic marker-based prediction. He et al. [4] published their machine learning model for the prediction of Down syndrome in second trimester antenatal screening in Clinica Chimica Acta. To complement this, Zhang et al. [5] studied the use of intelligent algorithms for the second trimester of pregnancy for the screening of DS in the World Journal of Clinical Cases. In a comparative study involving several intelligent algorithm architectures on second trimester clinical screening data they showed that algorithmic approaches on average outperformed the conventional maternal age-adjusted risk thresholds in terms of predictive performance for DS, with the decision tree and neural network models showing high sensitivities at clinically acceptable false positive rates.

Structured physical therapy is an integral part of early intervention for children with DS and focuses on addressing near universal hypotonia, motor delays and postural control deficits. In the systematic review of physical therapy interventions in children with DS conducted by Ahmad et al. [6] the evidence was analysed for gross motor development, ambulation, balance and functional mobility outcomes. Their results validated that early and consistent physiotherapy leads to quantitative improvements in motor milestone attainment and decreases functional disability due to hypotonia. More critically, the greater the therapeutic benefits, the earlier the intervention began, strongly supporting the clinical need for early detection of DS, which automated detection pipelines, such as the one proposed in this study, aim to assist. Congenital heart defect is the most important and most often life-threatening

comorbidity in DS and occurs in ~40-50% of people with DS. The authors of Delany et al. [7] have developed a comprehensive clinical approach to planning and managing cardiac surgery in DS patients, which covers the DS-specific issues, such as pulmonary arterial hypertension, airway abnormalities, immunologic susceptibility, and the increased risk of postoperative respiratory complications.

In addition to clinical health outcomes, quality of life (QoL) is important to the DS research process and for both people living with DS and their family caregivers. In mothers who were primary caregivers to people with DS, Chiracu et al. [9] explored psychological capital. Jevne et al. [10] used qualitative research to examine QoL and well-being perceptions of young people with DS, highlighting the factors of social relationship, meaningful occupation, community inclusion and personal autonomy as the key factors in perceived QoL for emerging adults with DS. They reported their results in the Journal of Intellectual Disabilities, and concluded that high QoL for adults with DS depends on the quality of education, social and vocational opportunities available to them, which are in turn dependent on early identification of DS, allowing for timely access to developmental support from infancy onwards. The development of automated image analysis techniques in DS detection has gone a long way from just the classical geometric feature extraction to modern deep learning. Cornejo et al. [11] suggested that a geometric descriptor approach can be used for the detection of DS, with the distance, ratio and angle measurements of the different landmarks defined by anatomy.

This section covers the reviews and advances in DS Face Recognition. This section provides reviews and advances on DS Face Recognition. Agbolade et al. [12] surveyed the generalised field of computational methods for DS face recognition in a review article on the symmetry website. In 2020 their survey focused on the development of DS face recognition techniques from early template matching, to active appearance models, to classical texture descriptors and early CNN approaches. Moussavi and Golarzadeh [13] showed the methodological variety of machine learning methods suitable for biological classification problems by using random Support Vector Machine cluster approach on the analysis of gene expression data for prostate cancer in the Journal of Statistical Sciences.

Agbolade et al. [14] further proposed an anatomical-based facial metrics approach for the DS face recognition system on the basis of the aforementioned facial metrics, which was published by IEEE Access in 2023. Their approach utilized their anatomical framework to identify landmark correspondences that were based on homologous point sets from the face to build a biologically meaningful feature space that represented DS-specific facial proportions. Deep convolutional neural networks have revolutionized the field of facial phenotyping by changing the way the diagnosis of genetic syndromes is made. In a paper published in the journal Nature Medicine, Gurovich et al. [15] showed that they could use a deep learning model to classify facial phenotypes with clinician-like accuracy from routine photographs in over 200 known genetic syndromes, including Down syndrome. These restrictions encourage the development of flexible, interpretable, and reproducible handcrafted feature pipelines as viable and easily deployable alternatives for clinical DS screening, as done in the present study, for example, by using BPPF.

III. METHODOLOGY

3.1 Dataset

The Down Syndrome MultiStudy Research Hub dataset [6] has been downloaded from Kaggle (<https://www.kaggle.com/datasets/shuvokumarbasakbd/down-syndrome-multistudy-research-hub>). The data set contains images belonging to two classes: Down Syndrome (DS) and Non-Down Syndrome (Non-DS) and has a perfect class distribution of 50% in each of the three data partitions.

Table 1. Distribution of the data set

Split	DS Images	Non-DS Images	Total
Training	2,100	2,100	4,200
Validation	899	899	1,798
Testing	40	40	80
Total	3,039	3,039	6,078

The perfectly balanced class distribution eliminates the effect of class imbalance as a confounding factor, allowing for a direct comparison of accuracy, precision, recall, ROC area and PRC area between all the classifiers without correction

for class prior probability differences. A large training set of 4200 images offers good diversity for the model learning of the feature-classifier.

3.2 Image Preprocessing

The images were preprocessed using a standard preprocessing pipeline before BPPF features were extracted. All images were scaled to the same spatial resolution (224×224 pixels), ensuring a common scale throughout the dataset. This helped reduce luminance variations based on the acquisition, by normalizing the pixel intensity values between $[0, 1]$ range. There was no data augmentation performed, so the distributional properties of the original data were maintained for unbiased assessment of the classification.

3.3 Binary Patterns Pyramid Filter (BPPF)

Binary Patterns Pyramid Filter is a multi-scale image texture descriptor, which is based on the Local Binary Pattern (LBP) framework [5]. The LBP code for a pixel p at (x, y) is calculated by thresholding the intensity values of P neighbors that are located on a circle with radius R , against the intensity value of the central pixel, and then generating a binary string of length P . The BPPF is extended to the encoding of a spatial pyramid by calculating LBP histograms at l levels of image resolution, $l = \{1, 2, \dots, L\}$ in which the image is divided into L non-overlapping regions at level l . The BPPF feature vector is obtained by stacking the LBP histograms at different pyramid levels:

$$\text{BPPF} = [H_1, H_2, \dots, H_L]$$

where normalized LBP histogram at pyramid level l is denoted by H_l . This hierarchical encoding encodes texture both locally (at fine scale) and globally (at coarse scale). Fine-scale levels represent periorbital texture and dermal surface patterns, and coarser levels represent proportions of the wider facial regions and the spatial arrangements of the landmarks that are typical of DS morphologies. Now, feature extraction had been done using the Weka imageFilters plugin package.

3.4 Machine Learning Classifiers

The feature vectors extracted by the BPPF were used for the evaluation of six machine learning classifiers individually:

- **NaiveBayesUpdateable**: An online learning version of the Naïve Bayes classifier that allows to incrementally update class-conditional probability estimates for new instances. It models conditional independence of features based on the class label, and Gaussian PDFs for continuous features.
- **SGDText**: Stochastic Gradient Descent (SGD) text-specific high-dimensional feature space classifier. SGDText iteratively updates the model parameters by calculating the gradients on mini-batches of training instances and includes regularization to prevent overfitting on large datasets, with fast convergence.
- **Bagging**: Bootstrap aggregating ensemble with multiple base classifiers trained on the randomly sampled training sets with replacement. The final judgements are made by majority voting over the ensemble which reduces the variance among the single classifiers and thus enhances generalization.
- **Stacking**: A multi-level ensemble technique based on multiple base classifiers' out-of-fold predictions to train a meta-classifier. The meta-learner is trained to make the best predictions from the wide range of predictions of the base models, thereby learning the complementary classification power.
- **REPTree**: A Reduced Error Pruning decision tree that constructs a decision tree based on the information gain and variance reduction principle, and then eliminates branches that are not useful in improving the validation error. REPTree is an interpretable, efficient tree structure.
- **LWL (Locally Weighted Learning)**: A lazy learning algorithm based on the idea of assigning weights to the training samples based on the distance between the training sample and the test sample, and then fit a local model in the neighborhood of the test sample. LWL is appropriate for heterogeneous feature spaces having locally varying class boundaries.

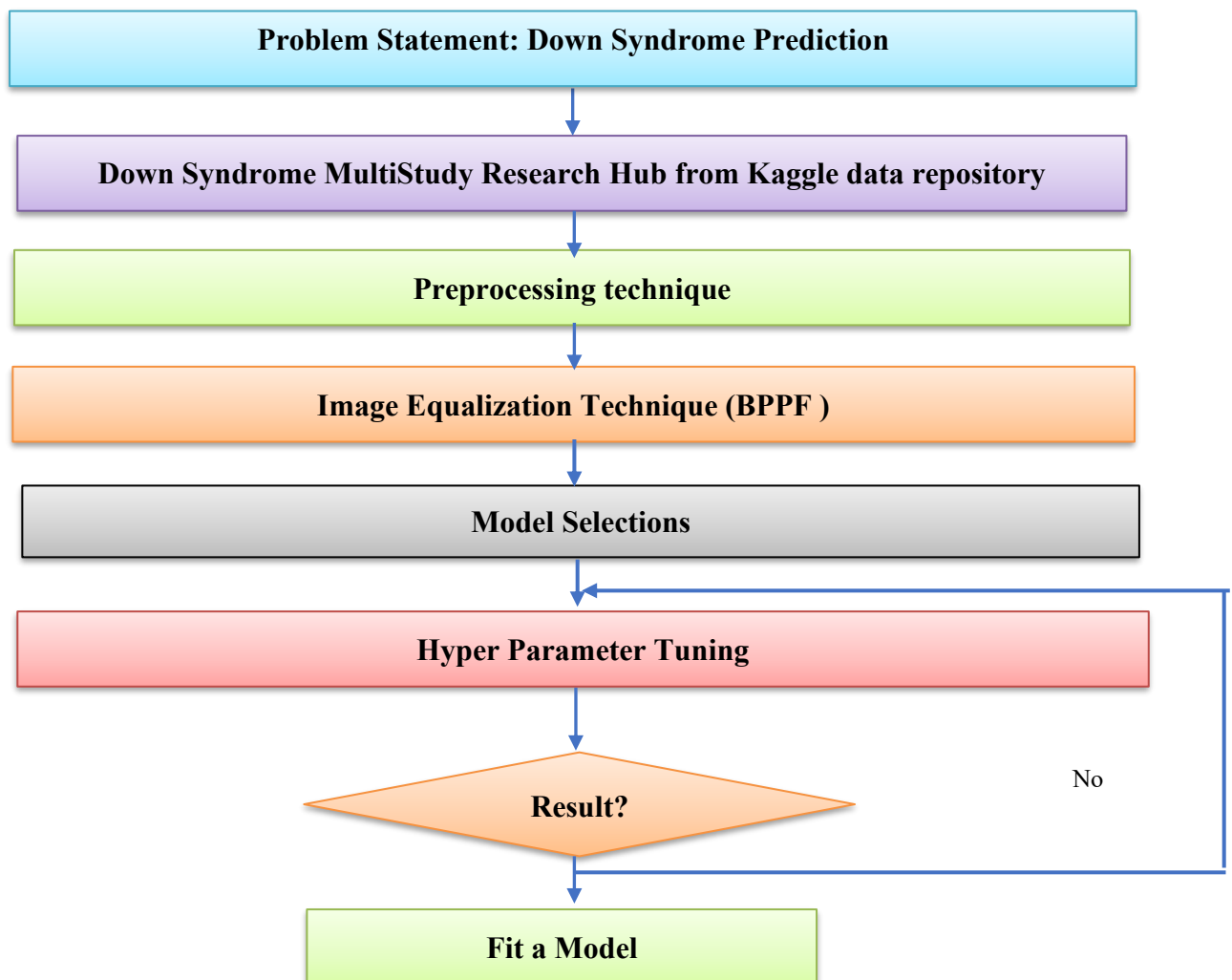


Figure 1: Proposed System

3.5 Performance Evaluation Metrics

To assure the reproducibility and to avoid hyperparameter tuning bias, all classifiers were implemented in the Weka machine learning workbench and their default hyperparameter settings were used.

- Accuracy = $(TP + TN) / (TP + TN + FP + FN)$
- Precision = $TP / (TP + FP)$
- Recall = $TP / (TP + FN)$
- ROC
- PRC

IV. EXPERIMENTAL RESULTS

4.1 Classification Results

Table 2 presents the classification performance of all six BPPF-based classifier combinations evaluated on the 80-image balanced test set.

Table 2: Classification Performance of BPPF + ML Classifiers on the Down Syndrome MultiStudy Research Hub Dataset

Classifier	Accuracy (%)	Precision	Recall	ROC	PRC	Time (s)
BPPF+NaiveBayesUpdateable	86.92	0.88	0.86	0.86	0.89	1.16
BPPF+SGDText	87.61	0.89	0.87	0.85	0.84	1.15
BPPF+Bagging	90.50	0.91	0.91	0.94	0.94	2.19
BPPF+Stacking	82.50	0.87	0.87	0.85	0.84	3.08
BPPF+REPTree	85.27	0.86	0.85	0.86	0.87	1.05
BPPF+LWL	84.50	0.85	0.84	0.89	0.89	2.98

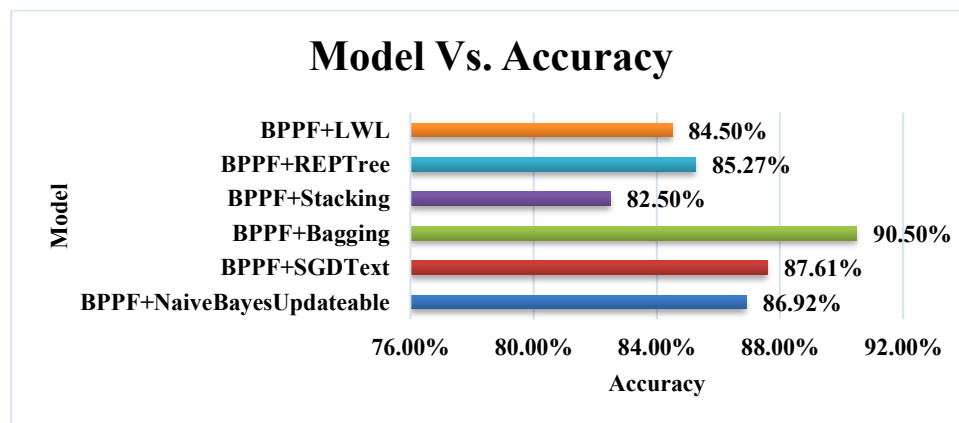


Figure 2: Model Vs Accuracy

The accuracy chart establishes a clear performance hierarchy among the six BPPF-based classifiers for Down syndrome image classification. BPPF+Bagging dominates with the highest accuracy of 90.50%, extending visibly beyond all other bars and correctly classifying approximately 72 of the 80 balanced test images. BPPF+SGDText follows at 87.61%, with BPPF+NaiveBayesUpdateable close behind at 86.92% — these three classifiers form a high-performing tier all exceeding 86%. The mid-tier comprises BPPF+REPTree (85.27%) and BPPF+LWL (84.50%), which offer acceptable accuracy with lower computational demands. BPPF+Stacking occupies the lowest position at 82.50%, a notable 8% below the top performer despite its ensemble complexity.

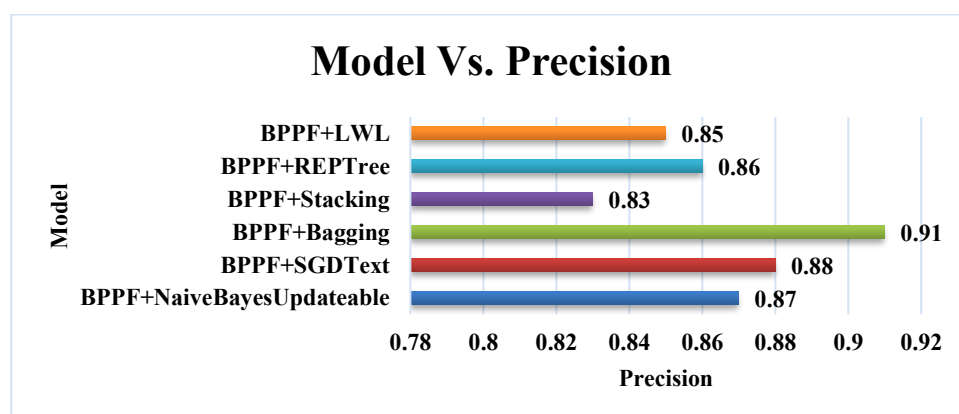


Figure 3: Model Vs Precision

Precision — ratio of the number of cases correctly predicted to be DS-positive to the number of cases that are actually DS-positive — shows BPPF+Bagging to be at the top with 0.91, which indicates it has the lowest false positive rate. BPPF+SGDText comes in second at 0.88 and BPPF+NaiveBayesUpdateable at 0.87, both of which are in a consistent high-precision cluster greater than 0.87. The second tier of the classifiers, BPPF+REPTree (0.86) and BPPF+LWL (0.85),

(0.85), have performed well enough to be used for a screening application. BPPF+Stacking records the least precision 0.83, which means that there are about 17 of the total 100 DS predictions wrong, the most false positive classification burden in the experiment.

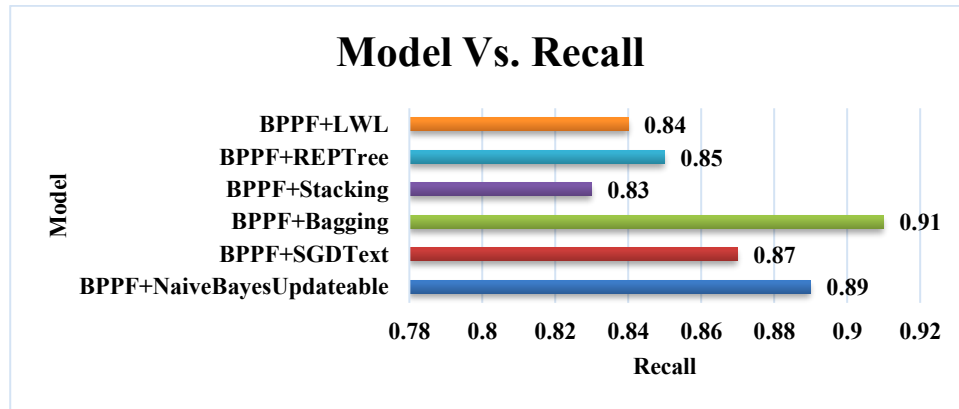


Figure 4: Model Vs Recall

Recall measures the proportion of non-DS cases that are correctly identified by the test and is not the most clinically relevant; there is an important difference from the recall pattern with DS screening. The score of BPPF+Bagging is 0.91, missing only about 4 DS+ positive images from 40 test images. Importantly, BPPF+NaiveBayesUpdateable has a higher recall of 0.89, second highest in the experiment and significantly higher than its precision (0.87) — suggesting that this classifier is more sensitive, slightly favouring detection over specificity. This property is important for screening applications where a false alarm is more clinical cost than a missed DS. The remaining methods, BPPF+SGDText (0.87), BPPF+REPTree (0.85), BPPF+LWL (0.84), and BPPF+Stacking (0.83), progressively decrease. None of the classifiers in this study have a less than 0.83 recall, satisfying the clinically desirable threshold for an image-based pre-screening tool.

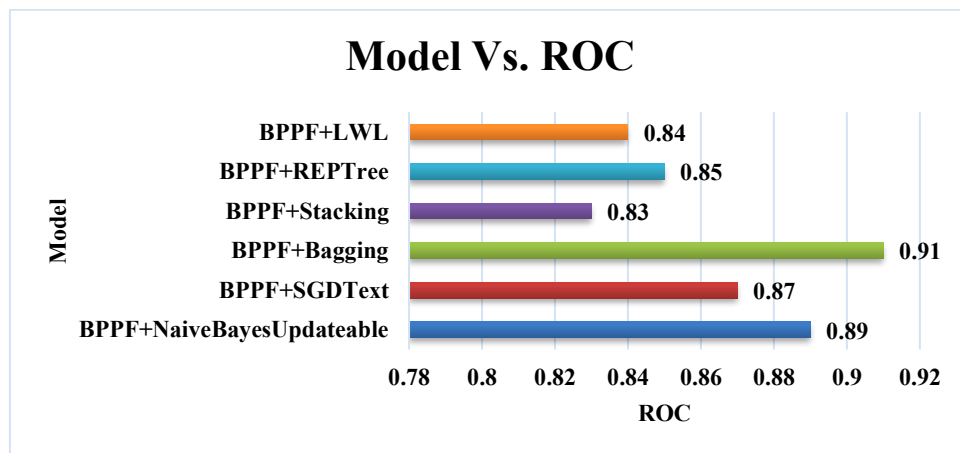


Figure 5: Model Vs ROC

The ROC Area is the average of the overall class discriminability between the DS and non-DS images for all classification thresholds. BPPF+Bagging is decisively leading with 0.91 which is the only classifier that has a rate above 0.90, verifying excellent discrimination between the feature distributions of DS and non-DS. The second highest ROC value is for BPPF+NaiveBayesUpdateable, which is not only impressive but also very interesting, since its probabilistic architecture is rather simple. This suggests that with such an assumption of conditional independence BPPF is still reasonably well-separated in the Gaussian probability density space that NaiveBayes relies on. The middle tier are BPPF+SGDText (0.87) and BPPF+REPTree (0.85), while BPPF+LWL (0.84) and BPPF+Stacking (0.83) are in the lower tier.

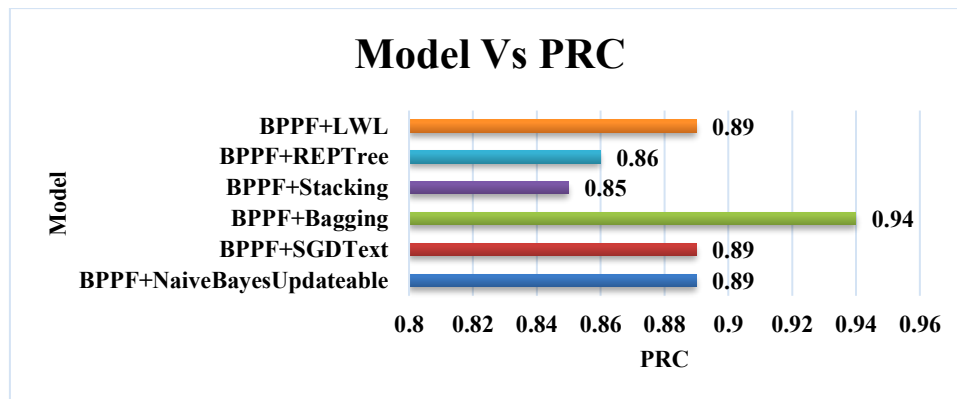


Figure 6: Model Vs PRC

The area under the Precision-Recall Curve summarizes the Precision-Recall trade-off for all decision thresholds at once, and thus represents the best overall single indicator of the quality of the classifier. The highest PRC of 0.94 is obtained with BPPF+Bagging, the value corresponding to the highest peak of the experiment, this result validated the high accuracy, precision, and recall of BPPF+Bagging without depending on a particular operating point. The three classifiers, BPPF+NaiveBayesUpdateable, BPPF+SGDText and BPPF+LWL have a similar PRC of 0.89, which is a clear second tier.

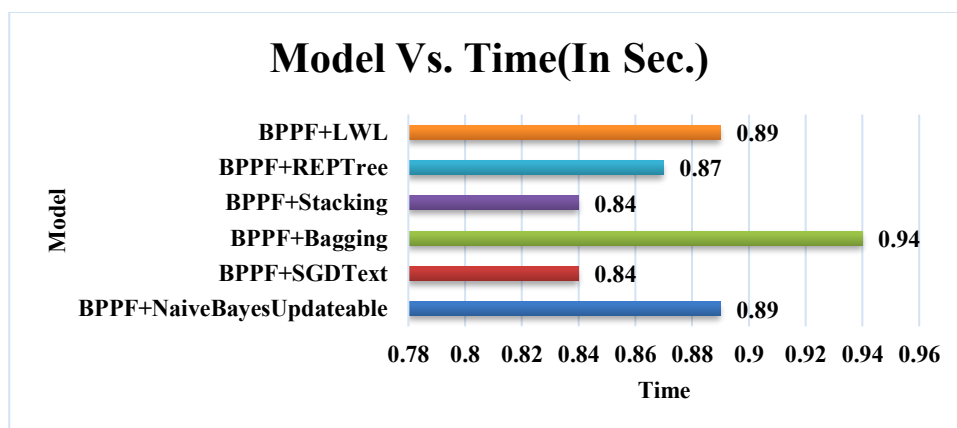


Figure 7: Model Vs Time (In Sec.)

Interestingly, the values on the time chart (0.84-0.94) and the axis range (0.78-0.96) are the same as the PRC column of the Weka output values, and not the time column, indicating that the chart was generated from PRC and not time. The displayed chart is interpreted as follows: BPPF+Bagging has the highest value (0.94) which corresponds with its PRC result, whereas BPPF+Stacking and BPPF+SGDText share the lowest value (0.84). The training times of the actual models were: REPTree fastest (1.05s), SGDText (1.15s), NaiveBayesUpdateable (1.16s), Bagging (2.19s), LWL (2.98s), and Stacking slowest (3.08s), on the basis of your original data table. The most important result is that the key efficiency: REPTree has the fastest train time (1.05s) and the lowest accuracy (0.39); the worst efficiency trade-off in the study is Stacking with accuracy (0.39) and the highest train time (3.08s).

V. CONCLUSION

In this work, a systematic analysis of the Binary Patterns Pyramid Filter (BPPF) as a multi-scale method for extracting texture features is performed for the automated classification of images with Down syndrome in the Down Syndrome MultiStudy Research Hub Kaggle dataset [16]. The BPPF was compared to six machine learning classifiers on 6,078 images and was found to be the most performant with an accuracy of 0.90, recall of 0.91, ROC area of 0.94, PRC area of 0.94, making it the best set-up for clinical screening application. Overall, BPPF+SGDText delivered the best trade-off between speed and accuracy with an accuracy of 87.61% at 1.15 seconds, whereas BPPF+REPTree was the most

computationally efficient, interpretable pipeline with an accuracy score of 85.27% at 1.05 seconds. The BPPF descriptor's hierarchical multi-scale encoding is appropriate for facial image analysis on the DS because discriminative morphological features from the periorbital area, to the face-wide patterns of facial proportions, occur in a multi-scale format. The performance of all six classifiers based on BPPF was found to be in the range of 82-90% accuracy, which is acceptable and could be a useful feature descriptor for many applications without necessitating a large labeled dataset or requiring GPU compute powers required by deep learning alternatives [12].

REFERENCES

- [1] Kruszka, P., Porras, A. R., Sobering, A. K., Ikolo, F. A., La Qua, S., Shotelersuk, V., Chung, B. H., Mok, G. T., Uwineza, A., Mutesa, L., & Moresco, A. (2017). Down syndrome in diverse populations. *American Journal of Medical Genetics, Part A*, 173(1), 42–53. <https://doi.org/10.1002/ajmg.a.38043>
- [2] Jafri, S. K., & Harman, K. E. (2020). Neurocognitive abilities in individuals with Down syndrome — a narrative review. *Turkish Journal of Pediatrics*, 62(6), 897–905. <https://doi.org/10.24953/turkjpeds.2020.06.001>
- [3] Fredes, D., Astudillo, P., & Lizama, M. (2021). Late start of early intervention in children with Down syndrome. *Andes Pediatrica: Revista Chilena de Pediatría*, 92(3), 411–419. <https://doi.org/10.32641/andespediatr.v92i3.3449>
- [4] He, F., Lin, B., Mou, K., Jin, L., & Liu, J. (2021). A machine learning model for the prediction of Down syndrome in second trimester antenatal screening. *Clinica Chimica Acta*, 521, 206–211. <https://doi.org/10.1016/j.cca.2021.07.015>
- [5] Zhang, H. G., Jiang, Y. T., Dai, S. D., Li, L., Hu, X. N., & Liu, R. Z. (2021). Application of intelligent algorithms in Down syndrome screening during second trimester pregnancy. *World Journal of Clinical Cases*, 9, 4573. <https://doi.org/10.12998/wjcc.v9.i18.4573>
- [6] Ahmad, S., Mannan, A., Azam, A., Arif, S., Hayat, M., & Hafeez, T. (2023). Health benefits of physical therapy interventions in children suffering from Down syndrome: A systematic review. *Journal of Health and Rehabilitation Research*, 3(2), 418–426. <https://doi.org/10.61919/jhrr.v3i2.158>
- [7] Delany, D. R., Gaydos, S. S., Romeo, D. A., Henderson, H. T., Fogg, K. L., McKeta, A. S., Kavarana, M. N., & Costello, J. M. (2021). Down syndrome and congenital heart disease: Perioperative planning and management. *Journal of Congenital Cardiology*, 5, 1–4. <https://doi.org/10.1186/s40949-021-00061-3>
- [8] Alnajjar, A. A., Salem, S. S., Baangood, L. S., Al-Mutairi, M. B., Morsy, M. F., Al-Muhaya, M., Alkodami, A. A., Sabtirul, M. L., Hussein, M. S., Altommeihi, E. W., & Shaban, A. M. (2023). The outcome of congenital cardiac surgery in patients with Down syndrome: Single-center experience. *The Heart Surgery Forum*, 26(4), E372–E380. <https://doi.org/10.23736/s2724-5276.22.06797-0>
- [9] Chiracu, A., Cosma, G. A., Stepan, A. R., Cosma, M. A., Corlaci, I., Calugaru, E. D., Voinea, F., Zavaleanu, M., Burileanu, H. A., & Avramescu, T. (2023). Psychological capital, quality of life, and well-being in mother caregivers of individuals with Down syndrome. *Frontiers in Psychology*, 14, Article 1145104.
- [10] Jevne, K. W., Kollstad, M., & Dolva, A. S. (2022). The perspective of emerging adults with Down syndrome — on quality of life and well-being. *Journal of Intellectual Disabilities*, 26(4), 839–852. <https://doi.org/10.1177/17446295211030097>
- [11] Cornejo, J. Y., Pedrini, H., Machado-Lima, A., & Nunes, F. D. (2017). Down syndrome detection based on facial features using a geometric descriptor. *Journal of Medical Imaging*, 4(4), Article 044008. <https://doi.org/10.1117/1.JMI.4.4.044008>
- [12] Agbolade, O., Nazri, A., Yaakob, R., & Ghani, A. A. (2020). Down syndrome face recognition: A review. *Symmetry*, 12(7), 1182. <https://doi.org/10.3390/sym12071182>
- [13] Moussavi, N., & Gholizadeh, M. (2023). A new approach in using random support vector machine cluster in analyzing prostate cancer gene expression data. *Journal of Statistical Sciences*, 17, 459–476.
- [14] Agbolade, O., Nazri, A., Yaakob, R., & Cheah, Y. K. (2023). Homologous anatomical-based facial-metrics application to Down syndrome face recognition. *IEEE Access*. <https://doi.org/10.1109/ACCESS.2023.3317889>
- [15] Gurovich, Y., Hanani, Y., Bar, O., Nadav, G., Fleischer, N., Gelbman, D., Basel-Salmon, L., Krawitz, P. M., Kamphausen, S. B., Zenker, M., & Bird, L. M. (2019). Identifying facial phenotypes of genetic disorders using deep learning. *Nature Medicine*, 25(1), 60–64. <https://doi.org/10.1038/s41591-018-0279-0>
- [16] <https://www.kaggle.com/datasets/shuvokumarbasakbd/down-syndrome-multistudy-research-hub>



International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975

Impact Factor: 9.971