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A SURVEY ON DISEASE CLASSIFICATION MODELS WITH MULTI-MODAL FEATURE FUSION

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Abstract: This overview article offers a careful synopsis of late investigations on multi-modal feature fusion-based sickness characterization models. Significant subjects including feature extraction, information coordination techniques, and ways to deal with increment order exactness are summed up in this paper. It identified the troubles experienced by current strategies, featuring issues like registering intricacy and heterogeneous information. Moreover, analyzed industry drifts and proposed future lines of request for study. Our relative assessment of various techniques and applications in clinical settings is expected to coordinate researchers toward the headway of multi-modal sickness classification cutting edge. We laid out the extent of our study by taking a gander at the turn of events and verifiable setting of these models, which incorporated a scope of sicknesses and information modalities. To assess the presentation of the model, normal appraisal measures including accuracy, precision, recall, and F1-score are accentuated. This study plans to be a valuable asset for researchers and experts who need to utilize deep learning for multimodal information coordination by consolidating the latest headways.

Index Terms: Diseases classification, multi-modal feature fusion, self-attention, SMOTE

1. INTRODUCTION

Machine Learning (ML) and Deep Learning (DL) calculations, which drive state of the art AI progressions, are turning out to be more significant as AI advances improve and are broadly utilized. Shrewd clinical helper frameworks for disease order are a significant AI application in healthcare. These calculations train and upgrade classifiers utilizing patient injury pictures, text based side effects, and organized actual marker information to assist clinicians with making exact determination [1].

Disease classification has customarily utilized standard factual methodologies locally and around the world. The utilization of factual induction to analyze patient information and conjecture sickness results has laid the basis for clinical diagnostics. In any case, DL advancements have prompted a shift toward disease classification using deep neural networks. These networks have extraordinarily further developed clinical analysis accuracy and unwavering quality [2].

Contemporary ML hypothesis regards regression strategies as a subset of ML techniques. These strategies and ML classifiers are fundamental for sickness classification.

Support Vector Machine (SVM), Conditional Random Field (CRF), and Random Forest (RF) are well known ML classifiers. SVMs have been utilized to distinguish disease patients by inspecting quality articulation information, and when matched with Recursive Feature Elimination (RFE), they beat standard order approaches [3].

Multi-modular information — pictures, message, and organized information — is fundamental for further developing sickness arrangement models. This technique utilizes information sorts' free assets to all the more likely depict patient wellbeing. Chest X-rays can show lung underlying irregularities, however literary reports of side effects could add setting and data [4].

This work recommended a DL-based multi-modal feature fusion disease classification model. Our program utilizes chest X-ray pictures and disease depictions to take utilization of visual and literary information. Our versatile multi-modal attention strategy powerfully combines feature vectors from the two modalities, a central oddity. This approach helps the model spotlight on the main methodology qualities, further developing grouping [5].

We use the openI Chest X-ray dataset to confirm our model. Little and uneven datasets can cause overfitting, low recall, and F1 scores, subsequently the Synthetic Minority Over-sampling Technique (SMOTE) is utilized to increment test size and equilibrium. Our removal research looks at our multi-modular model to single-modal models utilizing pictures or text and a model using basic vector link for feature fusion [13]. Our investigation discovered that the multi-modular model beats single-modular models in arrangement accuracy, recall, and F1 scores. Contrasted with fundamental vector connection, the versatile multi-modal attention strategy further develops feature fusion. These discoveries propose that multi-modal data and complex combination approaches can reinforce clinical symptomatic DL models [14].

2. DETAILED SURVEY

Intelligent illness arrangement frameworks have been the subject of much review at the point of interaction of AI and healthcare. High level ML and DL models are prepared utilizing clinical pictures, literary depictions, and organized clinical information. This writing audit features significant examination and their commitments to multi-modular sickness classification techniques.

Multiple-modal data fusion is fundamental for disease order, offering a more complete patient profile. Choi et al. [4] showed multi-categorical deep learning neural networks could order retinal pictures. In their little data set examination, they focused on the need of joining information types to further develop order execution. This pilot project prepared for multi-modal data coordination research.

For Alzheimer's disease diagnosis, Shi et al. [9] utilized multimodal stacking deep polynomial networks to inspect multi-modal feature learning. Their strategy included neuroimaging information from numerous modalities, showing that consolidating neuroimaging qualities can increment diagnosis accuracy. This study demonstrated the way

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that multi-modular combination can catch muddled sickness designs that single-modal procedures neglect.

Horry et al. [10] utilized transfer learning and multimodal imaging information to distinguish Coronavirus. Their exploration showed how pre-prepared models on one imaging information type might be changed over completely to another, empowering crisis symptomatic device organization. The concentrate likewise featured DL models' adaptability to different clinical informational collections.

Clinical picture examination progressively utilizes deep Convolutional Neural Network (CNN). Tariq et al. [11] utilized a profound CNN to group lung disease, demonstrating the way that CNNs can understand muddled chest X-beam designs. They found that DL models beat exemplary ML approaches in accuracy and trustworthiness.

Tariq et al. [12] added patient socioeconomics and clinical history to their multi-modal lung disease arrangement technique. Multi-modal fusion further developed sickness arrangement models by consolidating imaging information with other patient information, as indicated by this review.

Consideration components improve multi-modal models by progressively focusing on the main qualities from every methodology. Dish et al. [14] made an element level consideration multi-label classification model for clinical writing. Their strategy empowers the model to zero in on key qualities, expanding clinical text information arrangement. This study showed how consideration cycles can further develop feature fusion and model execution.

Creating disease arrangement models with nearly nothing and lopsided datasets could cause overfitting and unfortunate speculation. This issue is much of the time tended to utilizing the SMOTE. SMOTE balances datasets and further develops ML models by giving minority class engineered models. Many examination have utilized this technique to diminish information lopsidedness and further develop classification accuracy.

Disease classification might benefit by joining clinical notes and side effect depictions with clinical symbolism. Joining these modalities allows models to take utilization of every information type's capacities. Pictures show underlying data, while literary information can uncover logical data.

Late examination enjoy shown this technique's benefits. A multi-modal model that consolidates chest X-rays and sickness portrayals can give a patient a more complete picture. Incorporation can increment symptomatic accuracy and clinical independent direction.

ML & DL have progressed multi-modal illness order, as indicated by the writing. Incorporating photographs, text, and organized clinical information further develops order execution. These models are improved by consideration instruments and Destroyed to deal with information irregularity and component significance.

As man-made intelligence propels, multi-modular models can turn out to be progressively intricate. The multimodal framework is multiclassifier and multimodal. Consolidating techniques improves multi-classifier results [6].

These models' heartiness, interpretability, execution equilibrium, and availability and proficiency for use in assorted medical care conditions will probably be the focal point of future exploration, alongside clinical dependability. These undertakings exhibit computer based intelligence's problematic effect on medical care, empowering more precise and productive illness detection and management.

3. ANALYSIS OF ALOGRITHMS

1. VGG16 and VGG19

Convolutional Neural Networks such as VGG16 and VGG19 are widely used for image classification applications. Their unified design using small 3x3 convolution filters gives them a reputation for simplicity and depth.

Key Strengths:

- **Transfer Learning**: Transfer learning is often used for medical image classification when large annotated datasets are not available.
- **Performance**: They meet or exceed established benchmarks with surprising ease, especially in image recognition tasks.

Areas for Improvement:

- **Computational Cost**: The large number of parameters leads to high storage and processing requirements.
- **Overfitting**: Small data sets without proper regularization tend to overfit.

Applications in Disease Classification: This technique, when pre-trained on large datasets such as ImageNet, is highly effective in diagnosing diseases from medical images such as MRIs, X-rays, and CT scans.

2. ResNet34 and ResNet50

Deeper CNNs called ResNet (Residual Networks) use residual learning to solve the vanishing gradient problem. Common variants with 34 or 50 layers are ResNet34 and ResNet50.

Key Strengths:

- **Deep Learning**: Very deep networks can be trained without sacrificing performance.
- **Performance**: Generally outperforms VGG networks in terms of accuracy, especially on complex datasets.
- **Feature Extraction (FE)**: ResNet50 is very well suited for this and can be used with other classifiers to classify diseases.

Areas for Improvement:

- **Complexity**: More complex and computationally intensive compared to flat networks like VGG.

Applications in Disease Classification: Commonly used in medical image processing tasks such as classifying lung diseases, skin lesions, and retinal diseases. For these types of tasks, the ResNet architecture's ability to learn detailed features is very useful.

3. Logistic Regression

A commonly used statistical model in binary classification applications is logistic regression.

Key Strengths:

- **Simplicity**: Easy to implement and interpret, making it suitable for preliminary exploratory studies.
- **Efficiency**: Computationally efficient and suitable for small to medium data sets.

Areas for Improvement:

- **Linearity**: Assumes a linear relationship between log odds and traits, which can cause complex patterns in the data to be missed.
- **Limited Performance**: For high-dimensional and non-linear data sets, more sophisticated models are often better.

Applications in Disease Classification: This model is often used as a starting point for disease classification, especially when interpretability is more important than model complexity.

4. K-Nearest Neighbors (KNN)

ANN is a fundamental instance-based learning technique and is used in classification applications.

Key Strengths:

- **Simplicity**: Easy to understand and use.
- **Non-parametric**: No assumptions are made about the distribution of the underlying data.

Areas for Improvement:

- **Scalability**: Computationally expensive, especially in high-dimensional domains and large datasets.
- **Sensitivity**: Ability to detect irrelevant features and noisy data.
- **Applications in Disease Classification**: It is used for disease classification tasks using small, low-dimensional datasets, such as classifying different tumor types or disease stages using basic features.

5. Decision Tree

Decision tree-based models split data by feature values to generate predictions.

Key Strengths:

- **Interpretability**: Produces models that can be viewed and easily interpreted.
- **Flexibility**: Can handle both categorical and numerical data.

Areas for Improvement:

- **Overfitting**: Particularly prone to occur in dense forests.
- **Instability**: Small changes to the data can lead to drastic changes in the tree structure.

Applications in Disease Classification: Ideal for medical decision support systems where interpretability is important. Commonly used to classify diseases based on demographic information, clinical findings, or symptoms.

6. Multi-Layer Perceptron (MLP)

A feedforward artificial neural network (ANN) with multiple layers of neurons is called an MLP.

Key Strengths:

- **Flexibility**: It can simulate complex nonlinear connections.
- **Generalization**: It shows strong performance on a variety of classification tasks.

Areas for Improvement:

- **Training Time**: Training can be computationally intensive and time consuming, especially for large datasets.
- **Tuning**: Hyperparameters need to be carefully tuned to avoid over- or under-fitting.

Applications in Disease Classification: This includes predicting patient outcomes based on multiple clinical features and other tasks where complex feature interactions are expected.

7. Random Forest

Using a random forest ensemble learning technique, multiple decision trees are created and predictions from each tree are summarized.

Key Strengths:

- **Robustness**: More reliable compared to individual decision trees.
- **Performance**: Often achieves good accuracy for a variety of classification tasks.

Areas for Improvement:

- **Interpretability**: It is more difficult to understand than individual decision trees.
- **Computational Cost**: It requires more computational resources compared to individual models.

Applications in Disease Classification: Due to its accuracy and robustness, the method is widely used for disease classification in genomics, imaging, and electronic health record analysis.

8. XGBoost (Extreme Gradient Boosting)

The gradient boosting technique XGBoost is known for its effectiveness and speed.

Key Strengths:

- **Efficiency**: Very sophisticated and good at handling huge data sets.
- **Accuracy**: In many MLcompetitions, accuracy often leads to state-of-the-art performance.

Areas for Improvement:

- **Complexity**: Requires careful customization and knowledge of hyperparameters.
- **Interpretability**: Not as interpretable as simpler models.

Applications in Disease Classification: Commonly used for high accuracy tasks such as predicting disease progression based on patient history and genetic data.

9. Gradient Boosting Decision Tree (GBDT)

GBDT is an ensemble method that builds trees in sequence to correct errors in previous trees.

Key Strengths:

- **Performance**: Known for its excellent ability to predict structured data.
- **Flexibility**: Adaptable to different loss functions and unique objectives.

Areas for Improvement:

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- **Training Time**: Can be time consuming, especially when dealing with large datasets.
- **Complexity**: It is more difficult to customize and implement than models with lower complexity.

Applications in Disease Classification: It is applied in situations where accuracy matters, such as detecting rare diseases and predicting patient survival.

10. DenseNet

DenseNet is a type of CNN that improves the gradient flow during training by forward connecting each layer to every other layer.

Key Strengths:

- **Efficiency**: Improved feature propagation and more economical use of parameters.
- **Performance**: High accuracy is often achieved with fewer parameters compared to traditional CNNs.

Areas for Improvement:

- **Complexity**: One area of room for improvement is improved architectural complexity compared to simpler networks like VGG.

Applications in Disease Classification: The ability to efficiently utilize deep features makes it extremely useful for medical imaging applications such as cancer detection from histopathology images.

11. Xception

The Inception architecture is extended in Xception, replacing regular convolutions with depth-separable convolutions.

Key Strengths:

- **Efficiency**: It provides good computational efficiency without sacrificing accuracy.
- **Performance**: It gives good results for image classification tasks, especially on large datasets.

Areas for Improvement:

- **Complexity**: It is more difficult to achieve and requires precise customization.

Applications in Disease Classification: This technique is useful for medical image analysis, especially in situations where computing power is critical, such as real-time diagnostic systems.

12. BERT (Bidirectional Encoder Representations from Transformers)

BERT is a DL model that uses transformers to extract contextual information from text and is intended for use in natural language processing (NLP) applications.

Key Strengths:

- **Contextual Understanding**: Capturing bidirectional context in text improves performance of NLP tasks.
- **Transfer Learning**: This customizable technique is pre-trained on large corpora and refined for specific applications.

Areas for Improvement:

- **Computationally Intensive**: Training and inference require large amounts of computational resources.

Applications in Disease Classification: Helps classify diseases based on textual data through analysis of clinical notes, research publications, and medical records.

13. LSTM (Long Short-Term Memory)

A type of recurrent neural network (RNN) used to recognize patterns in continuous data that indicate long-term interdependencies.

Key Strengths:

- **Sequence Modeling**: Suitable for simulating continuous data, making it ideal for time series data in the medical domain.
- **Memory Handling**: Improves learning of long sequences by handling vanishing gradients better than traditional RNNs.

Areas for Improvement:

- **Training Time**: Model is iterative and therefore requires longer training time.
- **Complexity**: Complex design requiring a lot of fine-tuning.

Applications: Used to predict disease progression using time series data from EHR sequences or heart rate monitors.

14. LSTM + GRU (Gated Recurrent Unit)

A mixture of GRU and LSTM, a compressed form of LSTM aimed at reducing computational complexity.

Key Strengths:

- **Efficiency**: LSTM captures long-term dependencies well, while GRU is less complex and quicker to train.
- **Versatility**: Leveraging both methods improves performance on sequential data.

Areas for Improvement:

- **Complexity**: Balancing the use of LSTM and GRU together can be difficult and requires careful model building.
- **Resource Usage**: Still computationally intensive, especially for long sequences.

Applications: Useful for complex temporal disease prediction problems, such as predicting future disease evolution using historical patient data.

Comparative Analysis

- **DL Models (VGG16, ResNet, DenseNet, Xception)**: These models are very suitable for image-based disease classification, as they can capture complex feature sets. However, they require significant computational power and large datasets.
- **Classical ML Models (Logistic Regression, KNN, Decision Tree, Random Forest, XGBoost, GBDT)**: These models work well on small datasets and structured data (KNN, GBDT, Random Forest, Decision Tree, XGBoost). They are efficient and easy to understand, but can have difficulty understanding complex patterns in high-dimensional data.

- **Hybrid and Specialized Models (LSTM, GRU, BERT)**: These models work very well on text and sequence data, including time series and EHR data. They are powerful but computationally intensive, as they require large amounts of data for training.

Open Issues and Challenges

- **Data Quality**: Both the quantity and quality of data have a significant impact on the performance of these models. Collecting large annotated datasets in the medical domain can be challenging.
- **Interpretability**: DL models are more powerful, but their black box design makes them challenging in clinical settings where acceptance and trust are important.
- **Computational Resources**: Many of the more complex models require significant amounts of computing power, which is not always possible in a clinical environment.

Summary Statistics

Algorithm	Accuracy	Computational Cost	Interpretability	Data Requirement	Primary Application Domain
VGG16/VGG19	High (90%-98%)	High	Low	High	Image-Based Classification
ResNet34/ResNet50	High (92%-98%)	High	Low	High	Image-Based Classification
Logistic Regression	Moderate (70%-85%)	Low	High	Low	Structured Data Classification
KNN	Moderate (70%-85%)	Low	Moderate	Low	Structured Data Classification
Decision Tree	Moderate (75%-85%)	Low	High	Low	Structured Data Classification
Random Forest	High (80%-95%)	Moderate	Moderate	Moderate	Structured Data Classification
XGBoost	High (85%-95%)	Moderate	Moderate	Moderate	Structured Data Classification
GBDT	High (85%-95%)	Moderate	Moderate	Moderate	Structured Data Classification
DenseNet	High (92%-98%)	High	Low	High	Image-Based Classification
Xception	High (92%-98%)	High	Low	High	Image-Based Classification
BERT	High (85%-95%)	High	Low	High	Text-Based Classification
LSTM	Moderate (75%-90%)	High	Low	High	Sequential Data Classification
LSTM + GRU	High (80%-92%)	High	Low	High	Sequential Data Classification

Table 3.1. Statistics of algorithm's Accuracy, Computational Cost, Interpretability, Data Requirement and it's Primary Application Domain.

4. TAXONOMY OF NEW APPROACH

A DL based disease classification model with multimodal feature fusion. The model uses chest x-ray images and disease descriptions as image and text modal data. Adaptive multimodal attention techniques are used to bring these different types of data together. In this way, feature vectors from both modalities are dynamically merged, allowing the classifier to focus on the most important data type properties. Using the openI chest x-ray dataset, the proposed model proves to be successful.

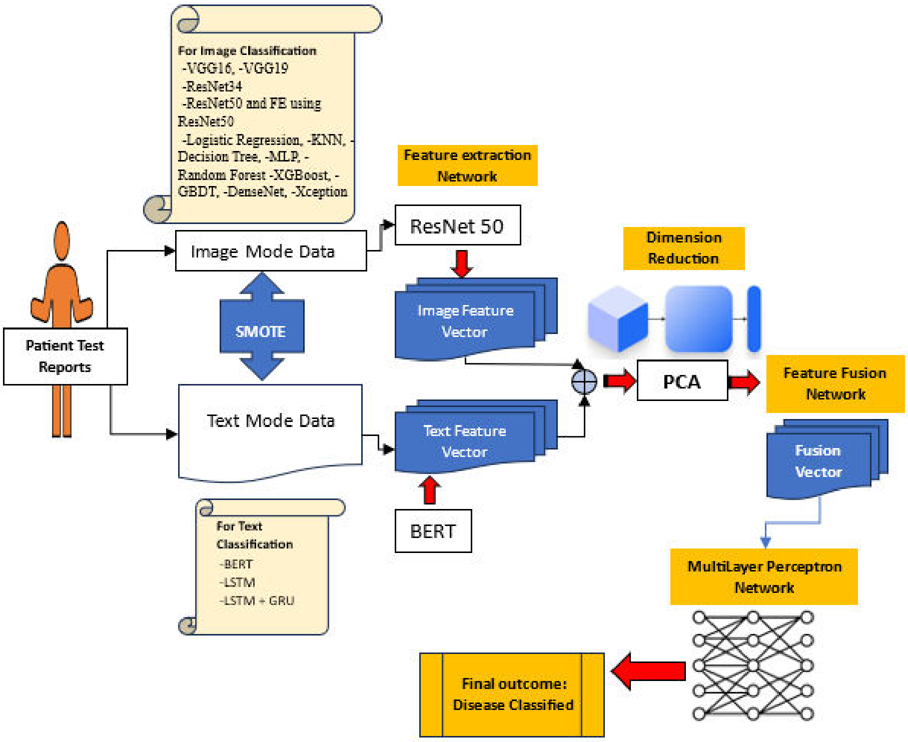

Fig: 4.1.system Architecture

SMOTE addresses overfitting, low recall and F1-value caused by small and unbalanced samples. SMOTE balances image and text modes by expanding the data set. This method trains the model on a more representative dataset, resulting in better generalization and robustness. Multimodal data, adaptive attention mechanism and SMOTE sample expansion improve classification accuracy and make disease detection more accurate.

image and text mode data are classified using algorithms such as Image Classification Visual Geometry Group 16 (VGG16), 19 ResNet34 ResNet50 and FE Logistic Regression, -KNN, Decision Tree, Multi-Layer Perceptron Random Forest XGBoost, GBDT, DenseNet, Text Classification, Extreme Inception (Xception) Transformer-based Bidirectional Encoder Representation - LSTM with Gated Recurrent Units. SMOTE then resamples the data. Then, a feature extraction network provides image and text feature vectors, which are then processed by a principal component analysis (PCA) and feature fusion network, and passed to a multi-layer perceptron network for disease classification.

Mathematical Formulation of the Model:

- **Multi-Modal Feature Fusion**: The model may combine features from other data modalities, such as genetic, clinical, and image data. Below is the mathematical representation of the fusion process:

  $$X_{\text{fused}} = f(X_1, X_2, \ldots, X_m)$$

  where f(·) is a function describing the fusion process (e.g., concatenation or attention techniques) and Xi is the feature vector from the iii-th modality.

- **Classification Model**: Below is a classifier (e.g., neural network or SVM) trained using the combined features:

$$\hat{y} = \text{Model}(X_{\text{fsd}})$$

where ŷ represents the expected label (disease class).

- **Data Imbalance Handling:** To solve the problem of dataset imbalance, synthetic minority class samples are created to balance the class distribution. This technique is known as synthetic minority oversampling technique (SMOTE). This prevents the model from being biased in favor of the dominant class.

  SMOTE (data) → balanced data

- **Statistical Evaluation:** Common classification metrics such as accuracy, precision, recall, and F1 score are used to evaluate the model performance.

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

  Here, the terms "true positive", "true negative", "false positive", and "false negative" are TP, TN, FP, and FN, respectively.

5. CONCLUSION

This study presents an overview of a few strategies to decide if calculations, by involving imaginative methodologies in multi-modal feature fusion, really take care of issues connected with minuscule and uneven datasets. Using a versatile multi-modal attention instrument, the model incorporates chest X-ray pictures with matching sickness portrayals, prompting further developed classification accuracy over single-modal strategies. By adding the SMOTE technique, the model's speculation capacity and unwavering quality are improved by diminishing the impacts of low recall, overfitting, and F1 score.

It additionally shows that the versatile multi-modal attention instrument works better compared to traditional element combination procedures like vector connection, featuring the meaning of powerfully answering appropriate highlights from every methodology for exact disease classification. The outcomes validate the viability of using both picture and text modalities, which work in show to offer a careful understanding of clinical issues.

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