Sentimental Analysis for Code-Mixed Language Using Deep Learning

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***Abstract— There are great challenges in sentiment analysis with widespread use of code-mixed languages in multilingual societies. The main difficulties found in separating opinions arise from increased language shifting, non-steady syntax and varying expressions of emotions conveyed through sarcasm and irony. The study suggests a hybrid model consisting of combining BiLSTM with attention mechanisms to establish nuanced contextual annotation, while at the same time, a strong transformer model like mBERT functions for the much-needed multilingual support. For training these models, annotated data was taken from Kannada-English and Hindi-English texts. The BiLSTM model scored an outstanding 94.8% accuracy and 0.91 F1 score, demonstrating its potential to handle complexities of code-mixed data but learns to build sentiment trends and linguistic patterns that can eventually lead to precise sentiment classification while correcting past failures. Comfortable with this model, it advocates for advanced sentiment analysis uses, including social media monitoring, customer feedback systems, and chatbot design supporting many languages to improve understanding and interactions of widely diverse linguistic contexts.***

***Keywords— Keywords— Sentiment Analysis, Code-Mixed Languages, BiLSTM, mBERT, Deep Learning.***

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# INTRODUCTION

Code-mixing, the practice of language, has been observed within almost every works on-the-ground, in manipulative ways, and even among the biases intertwined in the language. The form of code-mixing also helps to bring two or more speech forms about in grammatical structure, bilingually, bridging the gap across a longer and a lesser distance from the written aspect. Where the two or more languages slide distinctively side by side, multilingual activities, structures, and modalities get put in place to forget to pee into. Federal and joint attention of coding becomes known as complementary languages under its usual context for primary coding, but efforts to expose code are very confusing and embedded within the subcultures and vote out importance.

However difficult the current sentiment classification task may appear, and despite the wealth of tools for corrosion, code-mixing and other linguistic signals are critical to this task: code-mixing, unfortunately, needs lesser patterns, making it computationally harder for the machines dedicated to this functionality to produce accurate answers. Moreover, ML algorithms can be truly taught model Support Vector Machines (SVM) and Naïve Bayes may be the best as far as structured data is concerned but, as far as code-mixing is concerned, there will be an urgent need for further research. These algorithms will also suffer when the issue is defined more bifurcately between humans, but they go by a general, smart, and lazy approach to answer any question for anything in cyberspace. That is not how they function for humans——so far, that is. To increase the speed for real-time sentiment recognition, the cumbersome steps required for quantization and manual annotation form hurdles in quantizing sentiment. Thus, these are the motivating factors directly justifying that sentiment analysis in code-mixing languages should have a system designated to capture the essence of carrying on sentiment analysis in code-mixing languages..

# LITERATURE REVIEW

In the past decade, machine learning (ML) and deep learning (DL) approaches have made substantial advancements in detecting plant diseases while forecasting crop yields. Detection patterns within agricultural data by these models has enabled breakthrough improvements in farm productivity and crop management and sustainability efforts. Among all machine learning models for detecting plant diseases Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN) hold the leading position. Mathematical approaches with statistical functions and pattern matching technology scan plant health anomalies through images of leaves and stems and root systems to identify visual symptoms.

Ahmad G.I. et al., [1] provided a review of a number of machine learning and deep learning techniques used for sentiment analysis on a given set of code-mixed text from Indian social media. Of note in the review, among the traditional machine learning models, SVM, Naïve Bayes, and Random Forest are all being commonly used in the sentiment analysis area, whereas especially the SVM model works really well on a variety of datasets. Nevertheless, deep learning models such as LSTM, BiLSTM, and CNN produce acceptable results for noisy and unstructured data and hence have higher accuracy and F1 scores. It also advocates for the probable use of combination techniques when neural networks, including hidden layers for surface features, stitch together. Moreover, the review underlines that pertaining research has been on Hindi-English and Bengali-English pairs, whereas much less focus is given on the other Indian languages of Telugu, Marathi, and Kannada. Corpus annotation and pre-processing methods are the gaps that this study identified, as well as the need for more effective tools for parts-of-speech tagging in code-switching documents.

Ansari M.A. and Govilkar S., [2] proposed a sentiment analysis approach for transliterated Hindi and Marathi texts in mixed code scripts. The study combines supervised learning methods, including KNN, Naïve Bayes, and SVM, with ontology-based methods in a single model. The authors report achieving up to 90% accuracy for Marathi texts and between 80% and 90% accuracy for Hindi texts. Their contributions include developing a Marathi SentiWordNet and addressing grammatical challenges in mixed code text. The study paves the way for further research on multilingual transliterated texts in social contexts, with ongoing work to identify the best methods for translation.

Shahrin F et al., [3] employs machine learning algorithms to satellite imagery data to study agricultural output patterns while making harvest prognosis predictions. Research implements K-means clustering together with Mask R-CNN to track vegetation, but K-means demonstrates superior accuracy rates in change detection. Researchers employ machine learning models such as random forest and linear regression to make crop yield predictions and random forest demonstrates superior precision levels. The combination of time series models including ARIMA and LSTM produces improved modeling accuracy. Vegetation mapping through Python demonstrates superior outcomes in crop monitoring when compared to Matlab-based approaches.

Thirumal, S et al., [4 ] proposed a SCA-WRELM which brings together ELM with regularization methods and weighting functions alongside SCA optimization for enhanced rice crop yield prediction results. The framework exists to support yield forecasting accuracy in rice-producing South Asian regions because they require precise agricultural plans. This research uses SCA optimization on Weighted Regularized ELM (WRELM) parameters to achieve improved prediction accuracy which will deliver a dependable system for managing rice yields in dominant regions.

Choudhary, V et al., [5] Proposed a application of machine learning algorithms for plant disease prediction is examined in alongside the increasing popularity of AI in agricultural research. This research explores supervised, unsupervised and reinforcement learning model types which have proved applicable for agricultural challenges. The paper of Kim et al. (2020) combined with the work of Kranth et al. (2021) demonstrates how SVM, neural networks, Decision Tree, Naïve Bayes and Random Forest models successfully identify crop pests while Random Forest delivers the best predictive results among these approaches. The field of machine learning for agricultural disease prediction shows continuing growth potential because it provides important solutions for the industry.

Mehetre,S et al., [6] demonstrated how crop disease detection research progressed from using early models like the adoption of CNNs superseded previous agricultural applications of ANN and k-NN because these earlier tools had fitting challenges and processing problems in recent years. Early disease detection models achieved strong test results yet performed poorly with big datasets And generalizations. Research demonstrates that CNNs, specifically ResNet, established themselves as powerful solutions because of their distinctive approach to data processing,higher accuracy and better handling of large, noisy data. Models like VGG16 and EfficientNetModels were used for specific crop detection, but their effectiveness was restricted through limited input data and restricted focus scope.focus. Acceptable crop disease detection results come from the combination of CNNs, most prominently ResNet,generalized crop disease detection.

Lohi, S.A et al.,[7] distributed multiple crop disease identification models with upgraded classification technologies to enhance accuracy results. The models Unified Matrix-Based CNN (UMB CNN) and Leaf Wetness Sensor (LWS) demonstrate effectiveness for wheat and rice crops simultaneously face limits in their ability to scale across different agricultural systems. EfficientNet V2 performs disease detection tasks with both better accuracy and reduced computational complexity across various diseases. The Dilated Multiple Scaled AlexNet and Ensemble Nonlinear SVM and Augmented CNN and related models require large training datasets yet employ image segmentation techniques to boost their performance capability. The failure to implement feature selection technology prevents real-time applications.

Dhande, A et al., [8], presents the RoBERTa-BiLSTM hybrid model that will help in overcoming long dependencies, lexical diversity, and dataset imbalances while analyzing sentiment. The model makes use of RoBERTa for word embedding generation and BiLSTM for contextual semantics extraction from text. Experimental results show superior performance than the baseline models, which obtained an accuracy of 92.36% on the IMDb dataset and showed strong results on the Twitter datasets. Future work includes diverse datasets and fine-tuning hyperparameters to obtain enhanced performance.

Jim, J.R et al.,[9], reviews the latest progress in sentiment analysis with an emphasis on three main areas of improvement. Research examines ML based techniques alongside deep learning models LLMs and multimodal systems. The research looks at each approach's implementation methods, testing examples, and operational roadblocks. Through their innovative design BERT and RoBERTa transform the field by solving complex issues in transformer-based models. The research examines existing limitations in sentiment analysis from bias to domain adaptation while highlighting open challenges with current tools. Our goal focuses on solving these problems to develop better sentiment analysis systems. It studies how sentiment analysis works in different industries while looking at many application areas.

Nithyasundari, B et al.,[10] proposed HNNL utilizes deep learning methods for wheat disease verification. Recent deep learning techniques HNNL and CNN boost the ability to detect diseases in wheat crops. The identification of modern wheat diseases utilizes CNN technology, creating substantial improvements in diagnostic capabilities. HNNL allows us to detect diseases by integrating deep learning algorithms alongside pre-trained models to extract vital component features. The proposed solution includes running initial training processes to extract fundamental features. The HNNL approach demonstrates improved effectiveness when measured against other methods. Standard CNN systems prove excellent for classification tasks in disease detection. Data analysis of 1500 images across 12 disease categories including one control sample reached a 96.46% accurate classification accuracy. The dataset included one control sample and eleven disease types among its 1500 images. Repeated visual presentations of images originating from various perspectives, multiple whole-angle observations help improve the reliability of detecting disease categories. Evidence from precision/recall scores demonstrates that HNNL operates effectively, improving past results. The detection system performs better than CNN while demonstrating promise for automated wheat disease detection which provides continuous disease diagnosis.

Kancharagunta, K.B et al.,[11] proposed a research connects IoT instrumentation to machine learning frameworks to develop such systems. Extrapolated information arrives immediately following measurement outcomes. The system uses our system and evaluates soil quality through exams of nitrogen content and phosphorus along with potassium as well as pH values and humidity measurements and temperature records. Measure temperature plus environmental elements. We apply machine learning models. The processing methods utilized enhance decision trees and random forests within our system. The machine learning models trees and forests enable the analysis of data.  Models analyze past records in combination with current information to uncover relationships between variables. Through data analysis we can learn about these measurement influences on suitable crop selection. IoT sensors Live operational measurements emerge from environmental sensors which feed directly into our system. The system uses current farm measurements to generate instructions tailored to individual conditions. Precision farming decisions improve because of soil analysis optimization. The system delivers specific agricultural directions that help farmers maximize crop output together with smarter resource utilization by practicing sustainable farming practices. The system maintains simplicity for users as it supports connections with extensive device numbers. The system combines traditional agricultural methods with computational data to create personalized farm guidance. New methods for farming that improve both production levels and environmental protection have been developed.

Yadav, A et al.,[12] proposed a paper looked into the analysis of sentiments and hate speech in a code-mixed text Containing more than one language. Results showed better performance for the fine-tuned Bilingual model as opposed to the multilingual and monolingual models; this was based on Evaluation and development of bilingual LLMs for English-Hindi and English-Slovene. The Future work focuses on the testing of new language combinations and model specializations. Towards code-mixed contexts.

Islam, M.R. et al.,[13] integration of IoT and machine learning (ML) in agriculture has the potential to revolutionize farming practices by improving soil nutrient management and crop recommendations. Traditional methods of soil analysis and crop decision-making are often inefficient, relying on subjective assessments and labor-intensive processes. IoT-based devices, incorporating various sensors like moisture, pH, and nutrient sensors, provide real-time data on soil conditions. ML algorithms, such as random forest, logistic regression, and neural networks, process this data to offer tailored crop recommendations. These advancements enable precise, timely decisions, enhancing resource utilization, improving crop yields, and promoting sustainable agriculture. Additionally, field tests and mobile applications further empower farmers and consumers by improving transparency in the agricultural supply chain.

Ekanayaka et al.,[14] Proposed advanced system to monitor their crops while identifying any health issues in real-time.Crop diseases present an ongoing threat to agricultural production success and crop yield results. The worldwide food supply system remains endangered because of unsuccessful crop production.At present crops fail to perform as expected because diseases affect both production rates and farm revenue.Traditional disease diagnosis through inspections demonstrates both prolonged duration and substantial dependency on human judgment skills that produce errors. Environmental changes detect through IoT technology sensors enable measurement of environmental conditions.The system measures environmental factors through temperature measurements and soil moisture monitoring and humidity checks. The system uses sensors to monitor soil moisture together with temperature measurements to identify diseases at their earliest stages.The analysis conducted by machine learning algorithms searches through large datasets to detect distinctive patterns and symptoms that human analysts miss.The Random Forest Classifiers method achieves higher prediction success rates by finding problems early. Through electronic systems farmers gain access to essential data points which allow them to enhance their farming operation.Correct pesticide applications and water management practices under controlled farming settings allow farmers to observe crop diseases in developing stages.

Deshmukh, T et al., [15] gives a review of the machine learning approaches that can be applied to prediction systems using classification. From this research, draw the following conclusions.First, identify that there is not any existing system to give an alert to everyone who is engaged with the agriculture to be aware of new crop disease as soon as it arises. Second, go through related resources to get knowledge about crop diseases. Such as symptoms, other risky crops, disease types, and spreading methods. Finally, go through the most relevant research papers and review those based on the way of applying ML algorithms. The conclusion from that review is, that using an ensemble model that has a combination of two or more ML classification algorithms gives more accurate results rather than using a single ML classification algorithm.

Kumar, R et al.,[16] analyzes soil-water-air inputs to select best crops for growing and determine soil health status plus fertilizer needs. We offer fertilization advice based directly on soil testing results. We examine previous agricultural data and precipitation records for decision making. Our system successfully identifies which crops should be planted for an upcoming season at 85.55% determining harvesting times. The model analyzes soil nutrients to benefit sustainable agriculture and produce better harvests higher yields. This technology prevents crop losses and reduces waste of valuable resources to improve farming operations make everyday work processes run better. Through ML-based models farmers find the best crops for their needs to support higher income and resource conservation. The solution guides farmers to select proper crops which results in better yields and sustainable farming results for the future. The paper refers soil, weather, and water are key factors in effective agricultural planning, and recent advancements in machine learning (ML) are enhancing crop selection.

kumar Gajula, A. et al.,[17] proposed a system combines CNN technology to detect plant diseases with ML analysis to determine the best crops for specific soil conditions. Through ML evaluation of soil conditions this system suggests optimal crop types. Utilizing a dataset of 54,306.The CNN model shows 98.2% success at identifying 38 diseases affecting 14 different crops. Our system provides crop suggestions through K-means classification methods. The tool identifies crops that perform best under different conditions. The solution lets farmers guard their fields and determine proper crops according to soil conditions. Soil evaluation methods through machine learning identify optimal crops for better production and revenue results. Future advancements include by creating smartphone app versions of this system we aim to reach more farmers through user-friendly interfaces. We help people find solutions easily so they can decide wisely.

Vaishnnave, M.P et al.,[18] mentioned that factors such as soil nutrients (N, P, K, pH), temperature, and rainfall significantly affect production, and modern methods are required to replace traditional farming techniques. This study uses the KNN algorithm for crop and fertilizer prediction, addressing soil and climatic conditions for precise recommendations. Data preprocessing, feature extraction, and classification steps ensure accurate results. This approach empowers farmers to enhance yields, reduce costs, and promote sustainable agriculture.

Chana, A.M et al.,[19] proposed a system utilizes machine learning, specifically the Naïve Bayes classifier,to predict and recommend suitable crops based on soil parameters, weather conditions, and rainfall data. Data is collected from various sources like APMC, IMD, and farmers. Gov pre-processed, and categorized for training and testing. Feature selection and rainfall prediction are performed using correlation matrices and SVM, respectively. The model demonstrates a high accuracy of 97% in crop prediction. The goal is to assist farmers in maximizing crop yield and profitability by recommending the most appropriate crops for specific soil and climatic conditions. Future developments include an Android app or website for broader accessibility.

Senapati, B.R et al.,[20] explores the integration of IoT, machine learning, and weather APIs to enhance crop prediction and aid farmers in better crop selection. A prototype IoT device using sensors and APIs collects physical (N, P, K, pH) and virtual (temperature, humidity, precipitation, wind) data, communicating via the MQTT protocol. The Random Forest algorithm, achieving 99% accuracy, was applied to an 80-20 training-testing dataset. Predictions and recommendations were generated using cloud-based tools like Jupyter and Anvil. Field tests validated the model's effectiveness for both swampy and solid soils. Future improvements include extending weather forecasts to crop life cycles, adding more crops from local data, and allowing user-contributed crop data.

III. PROPOSED WORK

The research presents a modern agricultural system that melds IoT capabilities together with deep learning techniques supported by machine learning algorithms. The system uses IoT sensors to record current crop data as well as analyze disease conditions across the plants. Soil assessment through Random Forest and SVM machine learning deployment uses analysis of NPK measurements and moisture indicators together with pH tests along with temperature and humidity environmental assessments. A CNN model trains with leaf image datasets to deliver accurate disease detection. Soil data integration with plant images and weather patterns helps the system achieve better predictive accuracies together with enhanced reliability measures. These variables work in combination to provide exact sustainable farming practices which ensure operational simplicity while maintaining full process transparency.

IV. METHODOLOGY

The combined approach integrates IoT's data collection framework with machine learning technology to develop enhanced choices for disease management and crop variety selection. The implementation of IoT sensors enables the collection of real-time environmental and soil data which then uses preprocessing normalization and data augmentation techniques to create data stability. The combination of CNNs enables disease detection in leaves while crop recommendation models examine soil features. Applied trained models in specific agricultural setting deliver both precise outcomes with an expandable scope. The system connects various models using one structure which runs on Flask deployment framework for secure data storage. The computational method focuses on obtaining essential agricultural insights at lower computational levels to deliver results that enable farmers to scale productivity through accessible tools.

V. CONCLUSION

Agriculture is a key contributor to economic growth in India, and new data sources have expanded its scope. It introduces a new, efficient, and sustainable approach to help farmers by combining CNNs (for plant disease identification) and SVC (for crop advising) in a single use case. Additionally, data from NPK sensors and soil moisture detectors are collected by IoT devices at 2-second intervals, significantly improving the accuracy and usefulness of the system.

This end-to-ended framework helps the farmers with early detection of diseases in their crops, timely actions due to alerts and accurate crop recommendations based on soil and weather conditions. The intuitive web and mobile interfaces allow for accessibility, leading to easy adoption by various farming communities. Other add-ons, including disease forecasting, market price

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