# A Novel SynergyXLBi Model to Predict Personality Trait From Text Conversation

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***Abstract*— Social media platforms serve as powerful tools for communication and promoting justice worldwide. Nevertheless, identifying trustworthy individuals and assessing strangers on social media within a short time frame can be challenging. Deriving personality traits from digital content requires mapping textual data to a personality model. The widely accepted personality assessment model is based on the Big Five traits; however, existing algorithms like Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) have limitations. To predict personality traits, we utilize bidirectional context features and extraction methods with transformer-based models. Our proposed model, Novel SynergyXLBi, combines the capabilities of Bidirectional LSTM (BiLSTM), Generalized Autoregressive Pretraining for Language Understanding (XLNet) and Conditional Random Fields (CRF). It extracts features and leverages Named Entity Recognition (NER) to classify the Five Personality Traits (OCEAN). Experimental results demonstrate that the Novel SynergyXLBi model achieves an accuracy of 97.32%, precision of 97.21%, recall of 97.24%, and an F1-score of 97.11% when compared to Random Forest, K-Nearest Neighbors, Decision Tree, and K-means classifier models. We evaluated the performance using two state-of-the-art corpora namely CoNLL-2003 and WNUT-2017, and found that the proposed Novel SynergyXLBi model surpasses the performance of existing models.**

***Keywords*— *BiLSTM, CRF, NER, Novel SynergyXLBi, OCEAN, Personality Classifier, Personality Trait, social media, XLnet***

## I. Introduction

Over the past several years social media platforms have sprung up everywhere these days, almost completely reducing a human interaction to virtual spaces. This has given a rise to the trend of employing social media text data by researchers using state-of-the-art machine learning models for predicting user personality [1]. The knowledge of a personality is applicable in different areas, such as psychology or recommendation systems and decision making. In this research paper, the researchers are delving into a very interesting area of personality prediction. We nervously delve into textual data from social media, hoping to discover patterns that predict personality traits [2]. We placed a variety of studies under review to pull insights from our examination for the evolving terrain in personality prediction. The current world crisis has highlighted the need for a fuller health and well-being paradigm. Physical health is now the most important factor, and mental health though relevant to quality of life [3] is overlooked. Subjective well-being (SWB) is a good indicator of mental health. Nevertheless, questionnaires and other similar methods to assess SWB are constrictive in terms of time due to the variety of measures required for various purposes [4], which may not fully capture changes over a short-term period or based on day-to-day variability. So from here enters the game of Social Media- The digital ground to pen down your thoughts and feelings, one's experiences. Social media platforms produce huge amounts of daily textual data which can be an important source on personality analysis. Using machine learning algorithms we predict human personality traits from digital footprints [5].

The prediction of personality is a topic which has received an incredible amount of research attention, both for applications in areas such as recruitment [6], marketing and mental health. Our personality influences our behavior, preferences and how we make decisions [8]. This paper discusses the interesting field of personality prediction models, describes different methods and frameworks for such approaches as well as what are their implications [9]. The traits of personality have always seen to become significant for deciding various kind of dealings you will wish to make in life. And, companies have realized the importance of this facet more and more are combining personality profiles as part of their decision-making [10].

The present paper examines different personality prediction models, in addition to machine learning techniques and language-based implementations (i.e., pyschometric instruments). We explore the HEXACO model, Myers–Briggs Type Indicator (MBTI), and other pertinent paradigms. The objective is to offer an in-depth study on the contribution of these models for predicting personality traits.

The criterion for measuring personality is based on the OCEAN model, or else in Big Five Personality Trait (FPT) [11] as shown below table 1.

TABLE I. OCEAN DESCRIPTION

| Abbreviation | Description | Explanation |
|---|---|---|
| O | Openness | Encompasses characteristics such as insight, imagination, sensitivity, attentiveness, and curiosity. |
| C | Conscientiousness | Relates to care, discipline, deliberation, and diligence. Conscientious individuals are goal-oriented, exhibit self-control, and possess strong organizational skills. |
| E | Extraversion | Reflects emotional expression and assertiveness. Extroverts are outgoing, comfortable in social interactions, and often enthusiastic. |
| A | Agreeableness | Pertains to interpersonal harmony, empathy, and cooperation. Agreeable individuals are compassionate, cooperative, and considerate. |
| N | Neuroticism | Involves emotional stability versus instability. High neuroticism is associated with anxiety, mood swings, and emotional reactivity. |

Assessing personality traits has also evolved into a challenging field of interest, being explorative in nature with growing applications from areas like machine learning [7], linguistics or artificial intelligence (AI) [12]. Personality

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insight not only describes an individual's behavior but is also responsible for some vital decisions in multiple contexts as well [13]. This paper examines the most recent work in personality prediction models, detail their methods of development and practical applications as well as discusses new implications. This multidisciplinary field is comprised of different strategies: (i) Intelligent Edge Computing-Integrating edge computing and Machine Learning algorithms for predicting Myers Brigg's Personality type. A blend of personalized recommendations, which produces adaptive systems [14]. (ii) Historical Points of View - The alterations in personality characteristics between children and adults through centuries are shown by corpus linguistics. Language and language patterns provide us a window into the societal change index. (iii) Intellectual Humility: Investigating intellectual humility using AI, researchers identify high frequency terms, features and predictive models. It facilitated open-mindedness and self-awareness. (iv) Neural Networks: Using neural networks, authors automatized item creation in psychological scales [15]. Precision and efficiency in the development of Scale (v) Multimodal Analysis- group discussions yield gold data to estimate personality traits These approaches reveal individual variability when combined with multimodal analysis, as well. (vi) Large language models decode social media content and predict psychological traits Words and other linguistic cues provide an important aspect of user information available to social media sites [16].

Machine learning algorithms are then used to predict an individual's personality based on their behavior data from various social media platforms (e.g., Facebook, Twitter). Some examples of apps like, advertising that reads GK and marketer can design ads according to the personality. Personalized campaigns drive higher click-through rates and revenue [17]. They improve recommender systems with personality traits. Personalized recommendations work in all fields, be they suggesting movies to watch or music experiences and products. However, in the employment context social profiles are often solicited by companies wishing to vet potential job candidates for personality. Assigning tasks based on an individual fit the personality profile increases task efficiency and satisfaction [18]. In this work, we investigate the ability of natural language processing (NLP) techniques to predict personality from text without explicit measures thereof and consider how such inferences advance our understanding of influence between psychological traits. In the following sections, we will go through a literature review, what methods were used in those papers to predict personality and recalibrate our understanding of this brilliant area: Personality Prediction with further intrusive way.

In this paper, we propose a new model to predict personality using a hybrid BiLSTM-XLNet architecture. We address these limitations by integrating the explain ability features to maintain user trust, multilingual support for a wider cultural application and capable of analyzing longitudinal data that capture personality evolution. The merger is intended to foster a more inclusive and ethical model, ready for a wide range of use cases from personalized experiences, mental health care or better job candidate assessments.

## II. Literature Review

In our study, we performed a systematic review to synthesize the literature that focused on how text data can predict personality types. This post describes some of the datasets, feature engineering approaches, text mappings and AI models used for this. Importantly, it is still difficult to fit all personality traits into one model together. Regardless, our work demonstrates the possible utility of personality prediction in measuring SWB for individuals and groups.

Personality prediction from social media through machine learning: A comparison of various algorithms. The author Valanarasu [19], proposed a set of techniques using different machine learning methods to predict personality based on the behavior recorded in their public social traces. This could be implemented in an web application based recruitment. Utilize pre-trained language models and model averaging for personality prediction on text data from multiple social media sources [20].

Karanatsiou et al. [21] predict aspects of personality and relationship traits from social network data. According to their results, social media content is indicative of collective attributes and imitative traits in addition to personal characteristics. Exploring Machine Learning for Brand Personality Prediction through Social Media This indicates the possibility of social media analysis for monitoring brand image [22]. Yang, B.: Personality Prediction and Infer- ence through Text Analysis. Posted on by This showcases the increasing significance of deep learning models in this area. Aside from personality prediction, some works have also considered using social media data for chatbot customization [24]. There also seems to be work around predicting personality models on social media data, examples include the OCEAN model [25] and DISC framework [26].

In addition, studies are currently in progress on the relation between social media language and regional personality traits [27]. Many research works dedicated to personality recognition from user-generated content have been presented, that make use of methods like BiLSTM models with an attention mechanisms [28], [29]. The research statement in [30] finally examines the fusion of semantic structures and LSTM networks for personality prediction, implying that a combination may be an interesting possibility.

While much important work has been done on personality prediction with social media data a number of research gaps are left. As detailed previously, such limitations include lack of generalizability across platforms or brands, data privacy and user perception issues; as well explainable models and bias mitigation should be taken into account when developing new methods in this domain while considering questions regarding long-term effectiveness and overfitting compounded with the ability to leverage other available sources. We conclude by discussing potential areas for further research, including the analysis of regional dialects and other application tasks that extend beyond mood prediction, a refocusing on specific personality models when visualizing textual data, approaches to short text analysis in formal/semi-formal settings as well as ways to integrate sentiment analyses.

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## III. PROPOSED MODEL

Personality encompasses all the traits, characteristics, and quirks that make an individual unique. The whole thing from qualities, to characteristics and distinguishing personal characters in a person combined into one word personality. This encompasses of affective, cognitive and desire-behavior patterns as discussed in previous section. The significance of this research has much greater influence on quality of life and overall well-being that impacts the person as a whole. The Big Five divides personality into five broad dimensions of human personality (Neuroticism, Extroversion, Openness-to-experience, Agreeableness and Conscientiousness) which enable to predict behaviors based on social media text posts. Overview Researchers have investigated in Text from social media can be noisy, full of context, having diverse writing styles. The improved predictions via NLP & DL have made it possible for those strategies, and a proposed ensemble model Novel SynergyXLBi.

### A. *Novel SynergyXLBi*

Bi-LSTM as a type of RNN architecture is very frequently used in NLP tasks. The bidirectional LSTM takes advantage of both forward and backward LSTMs, it can understand context better as it sees the sequence one time from beginning to end (as a regular RNN) and the other from exist to begin. In the case of NER, Bi-LSTM can learn intra-word dependencies and give a better score by looking at left/right context simultaneously. Another model, XLNet is designed to extend BERT and GPT-3 in the class of pre-trained language models. While BERT uses a masked language model, XLNet is able look cross direction for words in sentence by virtue of considering all permutations and thus learning bidirectional context. Therefore, XLNet should be overall better since it is able to handle previously unseen entities more correctly due its autoregressive nature and the fact that NER tasks partially rely on this.

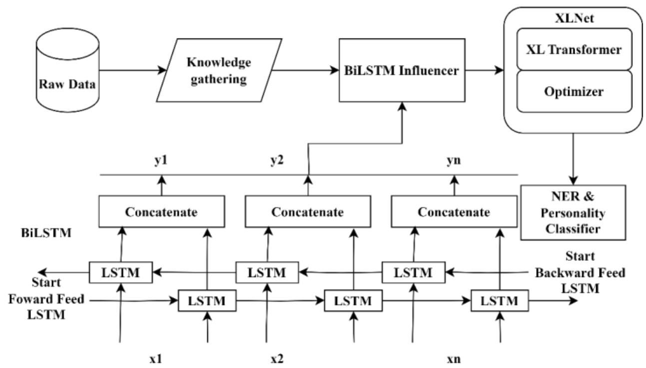


Fig. 1. Novel Synergy Model architecture and its internal components

Figure 1 shows the novel proposed SynergyXLBi model Full size image 1 is an ensemble method that consists of three stages: (a) sentence-feature extraction conducted by discriminatively pre-trained XLNet Models pretrained on a large corpus, which facilitates unsupervised learning (b) bidirectional processing performed by the Bi-LSTM model capturing context information from XLNet embeddings obtained in phase 1 to maximize long-distance dependencies between words and CRF-based stage(c),which identifies inter-label dependencies adjacent labels and guarantees consistent entity boundaries. The SynergyXLBi achieves state-of-the-art results on NER tasks, including the CoNLL-2003 English dataset and WNUT-2017.

### B. *Feature extraction*

The bidirectional long short term memory (Bi-LSTM) as a variant of the RNNs process sequences in two directions, it collects content information. Unprocessed raw social media text based conversation input sequence on the left side and [hidden states that are generated without forgetting any information discussed until now], which were processed using Forward LSTM, as well same Social media (process) input sequence but this time it is further reversed to match with Backward LSTM because we know how Recurrent neural network works; Left => Right ) mappings output generation. BiLSTM influencer: it concatenates the final hidden states from both directions (bidirectional representation) By taking into account past and future tokens, this extracts the contextual information features.

XLNet (Yang et al. The Sentence Word embeddings extracted from BiLSTM input, the Input text has been tokenized into sub word units Positional Encoding; each token will be embedded with positional info, as it's important to know where the tokens located. For every token, while the model is at each layer of depth from bottom to top XLNet computes self-attention scores using Self Attention Mechanism which allow it to consider all other tokens by attending them calculating contextual information. The threshold values can also (Be fine-tuned) through the self-attention layer stack to improve model performance;

CRF (Conditional Random Field) is part of the model and are primarily applied in NER for sequence labelling tasks using a probabilistic graphical model. This takes into account the dependencies between neighboring labels, and finds a path using transition probabilities from one label to another etc. also works globally for an entire sequence plain Find the best possible labeled sequence Viterbi algorithm.

### C. *Corpus and Experimental Set-up*

The classification task for the state of art used two standard datasets here i.e., CoNLL-2003 and WNUT-2017 dataset. The corpus was described in Table 2, where the attributes included: number of attributes, and other relevant parameters such as: size (attributes and instances), duration feature collected on every sentence based language use by source sentences base training file name.

TABLE II. DESCRIPTION OF CONLL-2003 AND WNUT-2017 CORPUS

| **Parameters** | **CoNLL-2003 dataset** | **WNUT-2017 dataset** |
|---|---|---|
| Attributes | Token ID (id), Token (string), pos_tags, chunk_tags, ner_tags | Id, tokens sequence, ner_tag sequence |
| Instances | 20744 sentences | 5690 sentences |
| Duration | August 1996 and August 1997 | 2017 |
| Language | English and German | English |
| Nature of sentences | Reuters news stories | context of emerging discussions |
| Corpus Size | 15.11MB | 2.55MB |
| Data Split | Training 14041, Validation 3250, Testing 3453 | Training 3394, Validation 1009, Testing 1287 |

The research set up was operated on a platform having the primary tensor core processing supported by NVIDIA GeForce RTX 3080 with 12GB VRAM. It also comes with

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an AMD Ryzen processor and 1Gbps internet connectivity. The software is in Windows 11 OS and for python supporting packages(photo)(TensorFLow, Keras, PyTorch,), Python 3.6 support, library dependent(use of other libraries) were implemented to develop a comprehensive software package. The proposed Novel SynergyXLBi model architecture comprises a neural network for NER. It involves an input layer, BiLSTM layers, batch normalization, global max pooling, dropout layers, dense layers, and an output layer. The BiLSTM acquires context from both the past and future symbols where batch normalization controls training and global max pooling decreases the sequence length dropout invades overfitting. It is followed by dense layers which convert the quantified pooled image and an output layer to generate NER forecasts, ReLU activation functions obtain solely positive improvements from the model.

## IV. Results

As a result, this architecture allows us to increase NER performance by employing forward and backward context information. It consists of the proposed Novel SynergyXLBi model Validation and Error results Table: The results of the novel SynergyXLBi model are a summary of the most intriguing and useful information from the results stream.

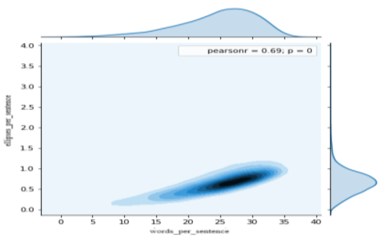


Fig. 2. Kernel density estimate correlation between sentence and personality

The plot is shown in figure 2 in the plot is the concentration of data at the edge of the lower ends of both axes, signaling that the vast majority of comments are of reduced magnitude and decide. It is significant to remark the ‘cluster’ or ‘hotspot’ in which the data point density is at maximum, approximately 5-10 words per sentence. The author has also written an annotation to state that pearsonr = 0.69; p = 0. In short, it shows that there is generally a moderate positive correlation between the no of words in a sentence.

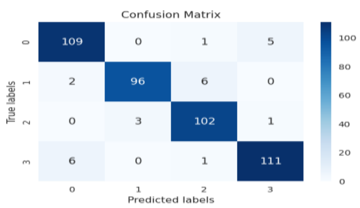


Fig. 3. Confusion Matrix of classifier: True Labels vs. Predicted Labels

Figure 3 depicts the confusion matrix, illustrating the no of the label forecast for each genuine label. The confusion matrix depicts the correct classification model’s performance with a group of outweighing data. The model predicted correctly that 109 cases belong to category 0, that 1 case that belongs to category 0 is expected to belong to category 1, and 5 cases that belong to category 0 are forecasted to belong to category 6. The model is performance validation predicts that 100 instances belong to class 6 by category 0.

TABLE III. Performance Comparison of Classifier models

| Classifier | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Random Forest [31] | 94.35 | 94.43 | 94.34 | 94.36 |
| KNeighbors [32] | 70.20 | 70.47 | 70.45 | 70.44 |
| Decision Tree [33] | 91.19 | 91.30 | 91.24 | 91.25 |
| K-Means [1] | 95.86 | 95.12 | 95.42 | 95.13 |
| Novel SynergyXLBi | 97.32 | 97.21 | 97.24 | 97.11 |

Table 3 compares the performance of different classifiers on different metrics. Table 3 gives a comparative in tabular form of five models which include Random Forest, KNeighbors, Decision Tree, K-Means, and Novel SynergyXLB. These classifiers are compared on the four metrics namely accuracy, precision, recall and f1-score. The numerical values specify the metrics of the classifiers for example Random Forest has an accuracy of 94.35% percent, precision and recall has the same output of 94.43% percent for precision and 94.34% for recall and F1-score is indicated by 94.36%, which is same output with other models. Meanwhile, our proposed Novel SynergyXLBi classifiers possess an accuracy of 97.32%, 97.21% precision, a recall of 97.24%, and 97.11% F1-score.

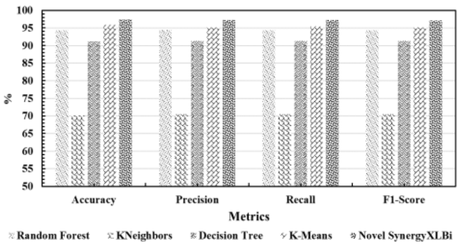


Fig. 4. Classifier Performance Comparison: Accuracy, Precision, Recall, and F1-Score among models

Figure 4 shows explains the model figures in terms of the percentage of accuracy, precision, recall and f1-score: Random Forest, K-Neighbors, Decision Tree, K-Means, and Novel SynergyXLBi. And graphically gives explanation pattern in percentage in decimal places from 0.50% -1.0%, the bars contain different shades to be represented differently.

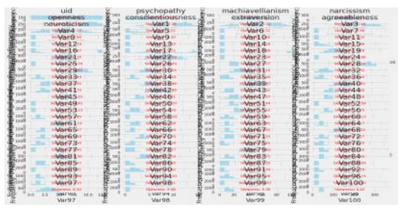

Fig. 5. Correlations Between Personality Traits: A Visual Matrix

Personality trait scores are presented in Fig. Each individual scatter plot is the x and y axis, representing which variables on at top or right of matrix. Fig 5 The axes go from -0.2 to 0.4 which implies they are standardized scores or correlation coefficients. In the other cells scatter plots are used again, because of its powerful ability to express both a relation between two variables as well how the distribution each variable in respect to amount.

This tree is known as a dendrogram and this visualization shows how the clusters are formed after Hierarchical

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clustering. Each clustering unit is represented by guide labels on the vertical axis of dendrogram, from 0 to 25 we can see how much similar. The Horizontal Axis, which denotes unlabeled observations that represent individual items or datapoints belonging to a cluster as in Fig. 6.

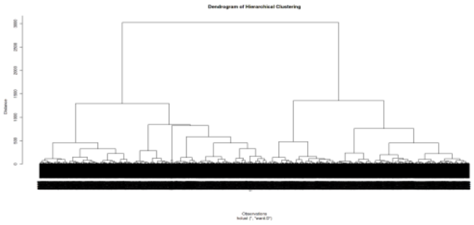

Fig. 6. Personality similarity based clusters

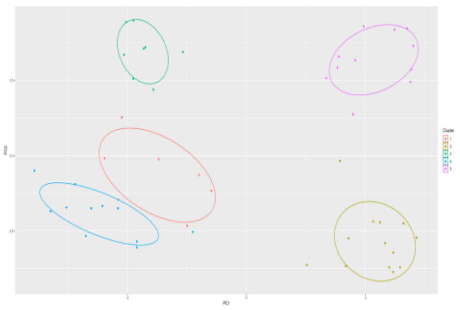

Fig. 7. Cluster formation using scatter plot

Two-dimensional scatter plot with various points, Fig. 7 Each of these colorful ellipses defines a distinct cluster consisting five groups or points red, yellow, blue purple and green. A cluster can be viewed as a group of data points which clump together and are quite similar to each other (meaning they lie close in the space defined) and this helps identify where pattern recognition lies for personality trait prediction.

## V. Discussion

According to table 3 numerical performance% the novel SynergyXLB had the highest values. Overall, Fig. 2 shows a modestly positive correlation between the word count per sentence and personality. The confusion matrix informs us that the model does quite well at predicting class 0 elements and even at classifying some classes from different categories as environment (class 5) items. The Fig. 4 Earlier the study has visualized complex statistical dependencies between 5 personality traits by any representation that should be suitable for psychological analysis standing OCEAN Five.

SynergyXLBi combines BiLSTM's capacity with text sequence learning, and enhanced XLNet permutation language modeling to potentially infer deeper personality cues in the provided texts. BiLSTM is great for capturing relationships among words in a sequence, and could deduce some personality traits that are conveyed through word order (sequential progression). On the other hand, we could really push performance on XLNet or any model that can understand how individual words relate to every word in a given sentence regardless of order. In this sense, SynergyXLBi is more adaptable across different types of text than MTBD only in terms of the data it requires - since it works exclusively with textual information there is a wider range and better quality available - but much easier to implement on many applications due to such light requirements. Second, working with textual data allows SynergyXLBi to extract personality traits as they are expressed in language. This could be especially useful in interpreting personality from online interactions where the external sources of knowledge are more restrictive. This mix of features makes SynergyXLBi a potential better solution for building text-based profiling.

In this research work, the proposed BiLSTM and optimized XLNet model with Novel SynergyXLBi for text-based personality prediction achieves substantial results. Our methodology builds on previous research in this area [35] but offers additional advantages. Thus, alongside ensemble modeling [34] and deep learning fusion approaches [36], SynergyXLBi incorporates the advantages of both BiLSTM sequential learning and XLNet permutation-language model to probe for more subtle traces of personality embedded within text. This work also improves over prior works in sentiment analysis [37] by leveraging refined XLNet, which is known for better representation learning with complex linguistic patterns such as those pertaining to personality traits. While KGrAt-Net [38] depends on external knowledge graphs, SynergyXLBi only considers textual data and can deliver a possible general approach. As prior work has also suggested deep learning as a good choice for personality prediction [23], it shows the validity of our findings, but to more extent this differ by pushing forward with an architectural solution tailored specifically to handle such information [39]. Further studies could investigate the integration of external knowledge sources together with SynergyXLBi to improve personality prediction accuracy [40]. In sum, our study suggests that SynergyXLBi has the potential of achieving even better text-based personality prediction and motivates future work along this direction.SynergyXLBi shows promise for increased personality prediction, but with limitations. Personality Prediction: SynergyXLBi only uses textual data for predicting personality. However, future work may also involve extending the available data to other sources of information (e.g., social network interaction or demographic characteristics), which could provide a more complete image of personality. Further research may involve experimentation with and perhaps re-calibration of SynergyXLBi in other domains to maximize effectiveness.

## VI. Conclusion

In this paper, we present the Novel SynergyXLBi model to predict personality traits using social media text. Combining BiLSTM, XLNet and CRF through bidirectional context features as well as transformer-based models. The model extracts the features and NER is used to classify personality traits Five Personality Traits (OCEAN) Experimental results show high performance, a mean accuracy of 97.32% across different angular image views with precision and recall both above 97%, yielding an F1-Score equal to or greater than the score for joint test data are presented. Crucially, the Novel SynergyXLBi model even beats SOTA models such as on CoNLL-2003 and WNUT-2017 corpora.

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