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Phrase Aspect Polarity Lexicon for Enhanced Multi-Aspect Polarity Extraction in Multi-Layer Form

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Abstract*—Feedback is indispensable for informed management decisions, but analyzing its can be challenging. That's where Aspect-Base Sentiment Analysis (ABSA) is very effective in finding valuable insights from text data. Polarity extraction is critical step in ABSA, which is performed using lexicon. However, current lexicon considers single word (unigram) often missing the context of phrase or compound term. This study propose a Multi-Layer Phrase Aspect Polarity Extraction using Lexicon (MLPAPEL), an n-gram-based lexicon designed to improve aspect-level sentiment analysis. MLPAPEL is inserted between pre-processing and polarity extraction in the ABSA framework. Plus, it compatible with popular public lexicons like SentiWordNet, AFINN, TextBlob, VADER and InSet. This study applies MLPAPEL performance to evaluate higher education feedback focusing in on areas like pedagogy, professionalsm, personality, socaial and facilities. They classified sentiment as positive, neutral or negative. The results found that MLPAPEL boosted F1-score across the board: 9.33% with SentiWordNet, 12.33% for both AFINN and VADER, 12.67% with TextBlob, and 9.33% for InSet. Additionally, MLPAPEL worked faster too, bumping up both precision and recall for aspect-level sentiment analysis. Ultimately, MLPAPEL isn't just another rule-based tool, but a new outomated approach to optimizing sentiment labeling in complex text, pushing ABSA forward both theory and practice.

***Keywords*—Phrase aspect polarity; lexicon; multi-aspect; extraction; multi-layer.**

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I. INTRODUCTION

These days, the rapid sepread of information, ideas, and communication among individuals from diverse backgrounds has resulted in an exponential growth of data sources. This flood of data plays a crucial role in management decision-making [1]. The rapid analysis of news in the financial sector particularly, is essential for traders, managers, and investors to make informed decisions [2]. Given the flood of textual data, efficient analysis methods are indispensable. Aspect-Based Sentiment Analysis (ABSA) has emerged as one of the most prominent techniques in recent years [3].

ABSA works in two main steps. First, it identifies the data into key aspects. Then it determines the data's sentiment based on those key aspect [4]. Either learning-based or lexicon-based methods can tackle these steps [5]. Learning-based approaches need a lot of labeled data and a large computing power [6], which can speed up the process [7]. On the other hand, lexicon-based methods offer a simpler alternative that requires neither complex infrastructure [8], or huge datasets but still manage to deliver better F1-scores [9]. The lexicon approach has proven particularly effective in enhancing text analysis models, demonstrating strong performance in tasks like emotion recognition [10] and depression classification in text [11]. For English, SentiWordNet, TextBlob, AFINN, and VADER are popular lexicons [12]. For Indonesian, there is the InSet [13] and SentIL lexicons [14]. However, most of these resources are generally for a word and a full sentence instead of finer aspects. To truly understand certain particular aspect of a sencence, additional techniques are required [15]. The standard ABSA model does not really have an additional method of optimizing the process.

Most existing lexicons struggle with multi-word expressions—things like phrases or compound words—which really matter to analyze text accurately [16], especially when it comes to grammar [17]. Phrase-level sentiment cannot be reliably determined by simply aggregating the polarities of individual words [18], as contextual elements like negators, intensifiers, and modals significantly alter sentiment intensity

[19] and may even reverse polarity [20]. This challenge is particularly relevant for Indonesian text data, where multi-word expressions are prevalent and often convey meanings distinct from their constituent words. For example, in the feedback *"perkuliahan jarang kosong"* ["lectures are rarely cancelled"], the phrase *"jarang kosong"* carries a positive connotation (implying discipline), despite both constituent words *"jarang"* ["rarely"] and *"kosong"* ["cancelled"] being negative in isolation. Similarly, in *"dosen memberikan banyak pengetahuan dan wawasan"* ["lecturers provide abundant knowledge and insight"], the entire phrase expresses positive sentiment (motivating). However, individual word analysis would not reveal this cohesive meaning that identifies the polarity. These examples demonstrate how current unigram lexicon-based approaches fail to capture phrase-level semantics, particularly given that much real-world feedback consists of unstructured or incomplete sentences.

To address these limitations, this study proposes an enhancement to the ABSA framework by inserting extraction-optimization process using multi-word lexicons to extract phrase-level aspect polarity across multiple extraction layers. The lexicons were structured based on phrase length, including two-word, three-word, four-word, and five-word expressions. Each lexicon consists of two columns: (1) phrases/compound words and (2) their aspect polarity classification according to predefined unigram categories (pedagogy, professionalsm, personality, social, and facility). The goal is to utilize these lexicons for phrase extraction and aspect polarity mapping, aiding interpretation with a standardized existing lexicon. The implementation followed a hierarchical approach, processing phrases from five-word to two-word expressions to prevent extraction conflicts and maintain the original polarity integrity for multi-aspect sentiment analysis accurately.

II. Materials and Methods

A. Aspect Base Sentiment Analysis (ABSA)

ABSA digs into text—like product reviews—and figures out how people feel about specific things like emotions and sentiment polarity. It classifies those polarity as positive, negative, or neutral [21] for specific aspects within textual data, such as product reviews [22]. The ABSA framework has five steps: collecting text data, cleaning up the text, detecting the necessary aspects, spotting the sentiment for each one, and then piecing the analysis together. A bunch of ways exist to perform this aspect identification task [23]. Aspect extraction, a core ABSA task can be performed using lexicon-based methods, machine learning, deep learning, or sometimes a combination thereof [24]. This study focuses on lexicon-based ABSA to enable more detailed sentiment analysis while addressing the limitations of unigram-based polarity extraction on sentences containing multi-word phrases.

Sentiment lexicons play a big role in NLP, especially in text classification. They are often paired with machine learning models, like CNN [25], LSTM [26], Decision Tree, Naive Bayes, and Support Vector Machine [27] to boost how well these models pick up on sentiment. The application of the pair cover a wide ranges of areas such as cross-lingual analysis [28], financial sentiment examination [7], and emotion detection [29]. The most popular public lexicon for English are SentiWordNet, TextBlob, VADER, AFINN, and Opinion Lexicon. There are also Indonesian versions like InSet and SentIL. Most of these lexicons just map words to their sentiment. Researchers usually mix them with other methods to dig deeper into the meaning of the text.

B. Experimental Data

This study uses student feedback data collected from a private universities in Yogyakarta, Indonesia in 2023, consisting of 3,216 entries with text lengths ranging from 1 to 62 words. Expert annotators categorized the feedback according to five key aspects: pedagogy, professional, personality, social, and facility. Each aspect was further classified by sentiment polarity as negative, neutral, or positive. The complete annotation for these aspect polarities are presented in Table 1.

TABLE I
ANNOTATION OF EXPERIMENTAL DATA

Polarity	Aspect				
	Ped	**Pro**	**Per**	**Soc**	**Fac**
Positive	1,946	729	904	627	310
Neutral	975	2,318	2,174	2,517	2,783
Negative	295	169	138	72	123
Total	**3,216**	**3,216**	**3,216**	**3,216**	**3,216**

Ped = Pedagogy, Pro = Professionalms, Per = Personality, Soc = Social, Fac = Facility

C. Framework of Enhanced Multi-Aspect Polarity Extraction using MLPAPEL

ABSA development typically involves several key phases: data preparation, pre-processing, aspect extraction, aspect polarity extraction, and evaluation [23]. Polarity extraction often uses publicly available sentiment lexicons such as VADER, SentiWordNet, AFINN, TextBlob, and InSet to spot whether something's positive or negative. Now, this study flips the script a bit. Right after the pre-processing, it drops in a new step: Multi-Layer Phrase Aspect Polarity Extraction using Lexicon (MLPAPEL). This step digs into phrases that the usual sentiment tools miss. Basically, it serves to replace phrases with inherently polar word that can be detected by the current sentiment lexicon unigram. MLPAPEL isn't just using a single dictionary, though. It stacks four phrase-level polarity lexicons—L5, L4, L3, and L2—one on top of the other (Figure 1). Thus, the updating ABSA framework looks like this: data preparation, pre-processing, phrase polarity extraction, aspect extraction, and finally, aspect polarity extraction.

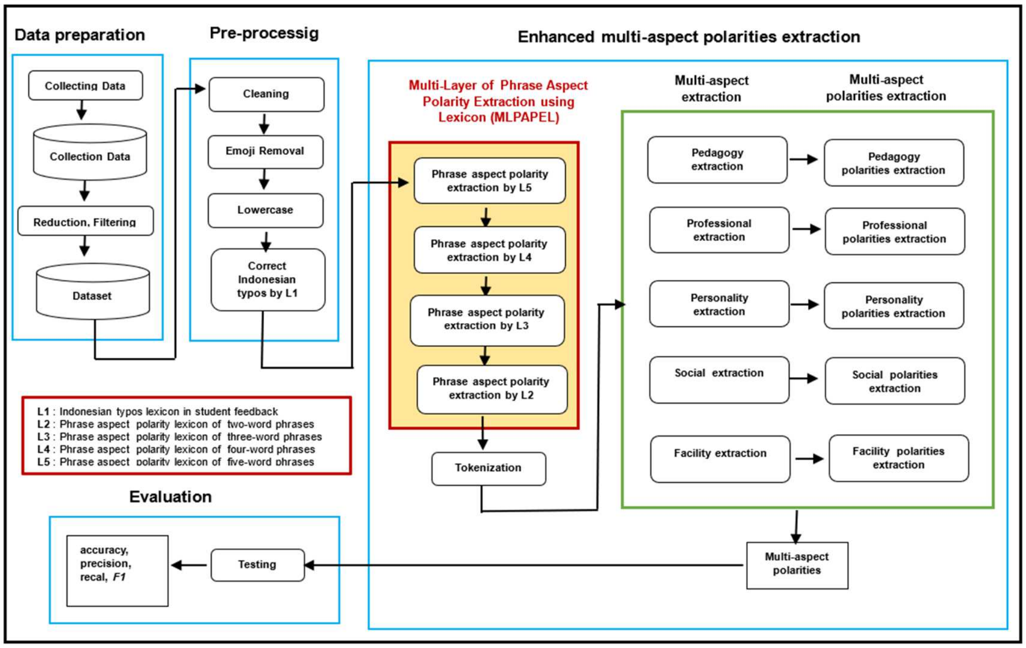

Fig. 1 Framework of enhanced aspect polarity extraction using MLPAPEL

The aspect lexicon (Table 2) is used for aspect extraction. For aspect polarity, we relied on the public lexicons listed in Table 3. This experiment categories aspect polarities into three buckets: positive, neutral, or negative. These lexicons give us a baseline to see how well MLPAPEL actually improves aspect polarity extraction accuracy. For the English lexicons as SentiWordNet, AFINN, TextBlob, and VADER, the data was translated them with the Google Translate API from the Pandas library to fit Indonesian data. The InSet lexicon, since it's already in Indonesian, didn't need any translation.

TABLE II
LEXICON FOR ASPECT EXTRACTION

Aspect Lexicon	Language	Number of words
Pedagogy	Indonesian	346
Professional	Indonesian	177
Personality	Indonesian	220
Social	Indonesian	179
Facility	Indonesian	136

TABLE III
LEXICON FOR ASPECT POLARITY EXTRACTION

Lexicon	Language	Proposed
SentiWordNet	English	2006
AFINN	English	2009
Textblob	English	2013
VADER	English	2014
InSet	Indonesian	2017

D. Phrase Aspect Polarity Lexicon for Extraction

This research developed four phrase aspect polarity lexicons by adapting Liang Xu's method (Table 4) [10]. Here's how it went: First, we put together a seed list of phrases. Then, we gathered and broke down the data. After that, we picked more phrases to grow the lexicon. We added those to the original list, and finally, experts looked over everything to make sure it worked.

TABLE IV
PHRASE ASPECT POLARITY LEXICON

Phrase aspect polarity lexicon		Language	Number of phrases
L2	Two-word phrases	Indonesian	518
L3	Three-word phrases	Indonesian	613
L4	Four-word phrases	Indonesian	151
L5	Five-word phrases	Indonesian	38

The aspect polarity lexicon has been categorized into four different lexicons based on the phase lengths, i.e., two-word phrases (Table 5), three-word phrases (Table 6), four-word phrases (Table 7), and five-word phrases (Table 8). Each of the lexicons includes two columns: 1) the phrases themselves, 2) their corresponding aspect polarities. The phase polarity refers to the sentiment orientation of a phase concerning different aspects such as pedagogy, professional, personality, social aspects, and facility. The lexicons have been employed to extract phrases within student feedback based on their explicit aspect polarities, which is a combined result of a multi-layered approach ranging from L5 to L2 to efficiently identify the phrases based on aspect polarity by focusing on the longest to the shortest phase lengths, i.e., five-word phrases, four-word phrases, three-word phrases, and two-word phrases, respectively.

TABLE V
TWO-WORD PHRASE ASPECT POLARITY LEXICON

Two-word phrases	Aspect polarity
banyak kendala [many obstacles]	*terkendala* [constrained]
cukup tegang [quite tense]	*tegang* [tense]
jarang kosong [rarely cancelled]	*disiplin* [discipline]
kurang asik [less fun]	*monoton* [monotonous]
kurang canggih [less sophisticated]	*jadul* [ancient]

TABLE VI
THREE-WORD PHRASE ASPECT POLARITY LEXICON

Three-word phrases	**Aspect polarity**
banyak jam kosong [lots of free hours]	*malas* [lazy]
bicaranya terlalu cepat [he talks too fast]	*gugup* [flustered]
cara menjelaskan baik [good way of explaining]	*jelas* [clear]
jarang ada kendala [there are rarely any problems]	*lancar* [fluent]
kadang susah sinyal [sometimes the signal is difficult]	*terkendala* [constrained]
kurang bisa dipahami [less understandable]	*sulit* [difficult]

TABLE VII
FOUR-WORD PHRASE ASPECT POLARITY LEXICON

Four-word phrases	**Aspect polarity**
cuma sekali masuk kelas [only went to class once]	*malas* [lazy]
kurang terdengar dengan baik [doesn't sound well]	*terganggu* [disturbed]
sangat mengerti akan mahasiswanya [very understanding of his students]	*peduli* [care]
tidak ada jadwal kosong [there is no empty schedule]	*disiplin* [discipline]
tidak terlalu mendalami materi [don't really understand the material]	*dangkal* [shallow]

TABLE VIII
FIVE-WORD PHRASE ASPECT POLARITY LEXICON

Five-word phrases	**Aspect polarity**
belum pernah memulai mata kuliah [never started a course]	*malas* [lazy]
memberikan banyak pengetahuan dan wawasan [provide a lot of knowledge and insight]	*memotivasi* [motivating]
tidak ada jam kuliah yang terbuang [no wasted lecture hours]	*efisien* [efficient]
tidak bisa membuat mahasiswa nyaman [can't make students comfortable]	*menyebalkan* [irritating]
tidak semua mahasiswa bisa mengaksesnya [not all students can access it]	*terkendala* [constrained]

The extraction process involves a phrase aspect polarity lexicon L, which consists of two columns: the first contains a set of phrases P, and the second contains the corresponding aspect polarities A. A mapping function $p(x)$ assigns each phrase $x \in P$ to its associated aspect polarity $a \in A$, as defined in Equation 1. For every $x \in P$, there is a corresponding $a \in A$ such that $p(x) = a$.

$$p(x) = aspect\ polarity\ of\ x\ on\ L \quad (1)$$

The lexicon L is used to extract the phrase's aspect polarity from student feedback. The function $e(x)$ is defined as a phrase aspect polarity extraction function, which maps a phrase $x \in feedback$ to its corresponding polarity using lexicon L, as specified in Equation 2.

$$e(x) = \begin{cases} x, & x \notin P \\ p(x), & x \in P \end{cases} \quad (2)$$

III. RESULTS AND DISCUSSION

Table 9 compares the feedback with MLPAPEL applied versus feedback without MLPAPEL. Feedback with MLPAPEL is more effective and effisient, because it is easier to extract aspect polarity using public lexicon, polarity detection got sharper, the polarity itself became clearer, and the feedback got shorter. All of this makes aspect polarity extraction more accurate. For example, the phrase "*jarang terjadi kendala*" (rarely encounter obstacles) was effectively mapped to "*lancar*" (smooth), clearly indicating positive polarity for the facility aspect. In fact, MLPAPEL can identify polarity even in phrases lacking obvious sentiment polarity. The phrase "*pengalaman yang belum pernah didapatkan*" ["an unprecedented experience"], while neutral when analyzed word-by-word, was correctly classified as positive for pedagogy when evaluated at the phrase level. Through the L5 layer processing, this phrase was condensed to "memotivasi" ["motivating"], explicitly conveying its positive sentiment. Furthermore, MLPAPEL improves text efficiency by summarizing multi-word phrases into single word that is a polarity terms. For instance, the 6-word phrase "*tidak membuat mahasiswa menjadi bosan*" ["doesn't make students bored"] was summarized to "*memotivasi*" ["motivating"], achieving a 4-word reduction. This summarization facilitates faster search processing while maintaining semantic accuracy, ultimately enhancing solution-finding efficiency.

This experiment shows that the performance of polarity extraction has been improved considerably, as depicted in the improvement of F1-scores for all the performance metrics depicted in Table 10. When MLPAPEL is used in conjunction with the baseline lexicons, high-performance classifications were achieved, with the maximum F1-scores ranging from 94% for SentiWordNet, AFINN, InSet, and 95% for TextBlob and VADER. This is indicative that the performance is optimal and the precision-recall trade-off is good. Moreover, the extent of performance improvement differs considerably among tools, ranging from 25% to 94% for SentiWordNet, 39% to 94% for AFINN, 30% to 95% for TextBlob, 39% to 95% for VADER, and 22% to 94% for InSet. This is due to the label imbalance in the dataset, as depicted in the graph in Table 1.

TABLE IX
RESULTS EXTRACTION USING MLPAPEL

Feedback	**Feedback with MLPAPEL**
tidak rumit [not complicated]	***gampang*** [easy]
baik dan ***tidak menyulitkan*** [good and not difficult]	*baik dan* ***bijaksana*** [kind and wise]
allhamdullilah dalam memberikan tugas ***tidak terus menerus*** [Thank God for not giving assignments continuously]	*alhamdulilah dalam memberikan tugas* ***bijak*** [Thank God for giving wise assignments]
cukup ***baik dalam membimbing*** *dan mengarahkan skripsi* [quite good at guiding and directing the thesis]	*cukup* ***memotivasi*** *dan mengarahkan skripsi* [quite motivating and directing the thesis]
selalu hanya mengirim materi dan ***tidak ada pembahasan lanjut*** [always just sending material and no further discussion]	*selalu hanya mengirim materi dan* ***acak*** [always send material and unstructured]
hal itu membuat banyak manfaat dan ***pengalaman yang belum pernah didapatkan*** *terutama pada gizi klinik rumah sakit* [it creates many benefits and experiences that have never been obtained, especially in hospital clinical nutrition.]	*hal itu membuat banyak manfat dan* ***memotivasi*** *terutama pada gizi klinik rumah sakit* [it creates many benefits and is motivating especially for hospital clinical nutrition]
pembelajaran asik ***tidak membuat mahasiswa menjadi bosan****, dan pembelajarannya* ***tidak banyak bertele tele*** [fun learning does not make students bored, and the learning is not long-winded]	*pembelajaran asyik* ***variatif*** *dan pembelajaranya* ***mudah*** [fun, varied learning and easy learning]

TABLE X
F1-SCORE OF ASPECT POLARITY EXTRACTION USING MLPAPEL

Lexicon	Polarity	Pedagogy		Professionalism		Personality		Social		Facility	
		NL	ML	NL	ML	NL	ML	NL	ML	NL	ML
SentiWordNet	Positive	83%	**84%**	72%	**73%**	69%	**79%**	73%	**79%**	60%	**64%**
	Neutral	63%	**67%**	89%	**89%**	89%	**93%**	94%	**94%**	93%	**94%**
	Negative	33%	**43%**	26%	**38%**	11%	**25%**	13%	**26%**	33%	**40%**
AFINN	Positive	80%	**83%**	70%	**72%**	70%	**77%**	77%	**81%**	59%	**63%**
	Neutral	63%	**65%**	88%	**89%**	88%	**91%**	94%	**94%**	94%	**94%**
	Negative	31%	**52%**	22%	**39%**	18%	**48%**	20%	**46%**	40%	**48%**
Textblob	Positive	82%	**84%**	73%	**75%**	73%	**80%**	79%	**83%**	60%	**66%**
	Neutral	62%	**66%**	89%	**90%**	89%	**92%**	94%	**95%**	93%	**94%**
	Negative	42%	**57%**	29%	**53%**	17%	**45%**	24%	**30%**	38%	**44%**
VADER	Positive	85%	**86%**	73%	**74%**	74%	**81%**	80%	**84%**	64%	**66%**
	Neutral	65%	**67%**	89%	**89%**	89%	**92%**	94%	**95%**	94%	**94%**
	Negative	44%	**53%**	29%	**39%**	19%	**49%**	28%	**42%**	44%	**48%**
InSet	Positive	**54%**	53%	47%	**47%**	47%	**60%**	46%	**50%**	45%	**47%**
	Neutral	59%	**62%**	88%	**89%**	89%	**94%**	93%	**94%**	93%	**94%**
	Negative	**25%**	24%	20%	**23%**	12%	**22%**	11%	**12%**	29%	**32%**

NL=Non-MLPAPEL, ML=used MLPAPEL

Figure 2 depicts the impact of MLPELAP on the various aspects, and it can be analyzed that personality exhibited the highest improvement in F1-score, followed by social, pedagogy, professionalism, and facilities. On the other hand, the outlier within this pattern is InSet, and at the same time, quite a noticeable enhancement for AFINN can be obtained with the inclusion of MLPAPEL. These figures establish the usefulness of MLPAPEL in the optimization of aspect polarity extraction.

Based on the comparative analysis done in Table 11, it shows that the accuracy of aspect polarity extraction for all lexicons can be improved with the addition of MLPAPEL. Also, all results showed improvement over baseline performance for each of the aspect categories individually. More interestingly, the results showed that MLPAPEL systems performed extremely well in that all accuracy levels were above 80%, showing that errors occurred less often and that MLPAPEL reduced these errors significantly. This confirms that MLPAPEL plays an essential role in improving the optimization of an aspect polarity extraction system using a lexicon.

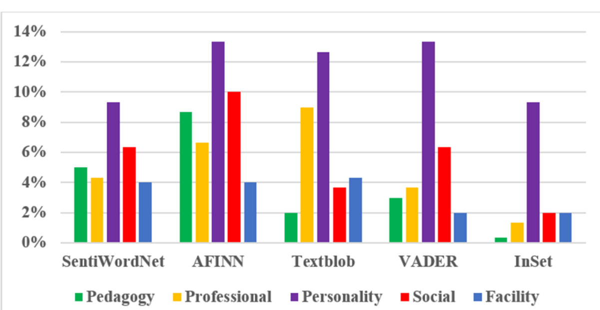

Fig. 2 Enhanced F1-score of aspect polarity extraction using MLPAPEL

Figure 3 describes the improvement in accuracy that is attained using the proposed approach in the task of aspect polarity extraction subtask. Among various aspects, personality showed higher improvements in accuracy compared to others. The second-best was pedagogy. The comparative study showed that the best lexicon in handling all aspects was SentiWordNet, followed by TextBlob in terms of accuracy improvements. All of the above experimental results showed the overall effectiveness of the proposed approach.

The efficiency and accuracy of current lexicon-based polarity extraction techniques are greatly increased by the incorporation of the phrase aspect polarity lexicon into MLPAPEL. In contrast, earlier methods were restricted to sentence-level analysis [18]. TThe extensive collection of annotated phrases in the comprehensive lexicon allows for granular aspect-level sentiment analysis. Compared to traditional phrase lexicons that only concentrate on polarity classification, the system performs better in extracting subtle aspect polarities from public sentiment data [30]. These findings support prior research [16], [17], on the importance of phrase-level analysis while extending their work through n-gram incorporation (beyond just bigrams), as suggested by [31]'s findings on phrase-based improvements.

Three major innovations in the implementation of MLPAPEL improve multi-aspect polarity extraction: (1) shorter processing time, (2) higher extraction accuracy, and (3) a new rule-based framework for automatic multi-aspect labeling. Each of detection approaches is optimized using MLPAPEL, and then fuse public sentiment lexicons for polarity recognition and aspect lexicons for feature extraction in a synergetic manner. ABSA has made considerable improvement over such integrated framework, particularly in the processing of complex aspect multi-word expression (MWE) in different domains. However, it is notoriously time consuming and also challenging to build up a phrase level aspect polarity lexicon through manual efforts.

TABLE XI
ACCURACY OF ASPECT POLARITY EXTRACTION USING MLPAPEL

Lexicon	Pedagogy		Professionalism		Personality		Social		Facility	
	NL	ML	NL	ML	NL	ML	NL	ML	NL	ML
SentiWordNet	71%	**75%**	81%	**83%**	81%	**86%**	87%	**90%**	86%	**88%**
AFINN	70%	**74%**	81%	**82%**	82%	**86%**	89%	**90%**	88%	**89%**
Textblob	73%	**76%**	82%	**84%**	83%	**87%**	89%	**91%**	87%	**89%**
VADER	75%	**77%**	82%	**83%**	83%	**88%**	90%	**91%**	88%	**89%**
InSet	47%	**47%**	71%	**72%**	74%	**79%**	80%	**81%**	83%	**85%**

NL=Non-MLPAPEL, ML=used MLPAPEL

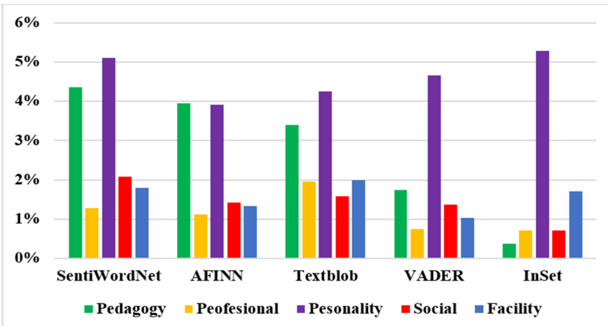

Fig. 3 Enhanced accuracy of aspect polarity extraction using MLPAPEL

The MLPAPEL model uses a dedicated phrase lexicon that has been specifically developed for processing student feedback, and is not generalisable to other domains. Its extension to other domains should involve construction of domain-specific lexicons, which is in the line discovered by studies emphasizing the domain specificity of lexicon acquisition [32]. This involves some serious difficulties when transferring knowledge between different areas of application. The tropical cyclone name generator currently uses a laborious, handcrafted lexicon that we created from numerous sources as part of the current development cycle. However, two limitations can be pointed out here: firstly, the system is now not yet in a position to "understand" the implicit meaning of words when formulated in sentences; and secondly, the lexicon should always be subject to a process of enlargement and _been updated in order to remain relevant as the data expands exponentially.

IV. CONCLUSION

This work enhances the ABSA framework by introducing a dedicated phase for phrase-level aspect polarity extraction using MLPAPEL as a novel approach. The implementation of MLPAPEL in stage 3 optimized aspects of polarity extraction in stages 4 and 5 of the ABSA framework as a research contribution. The enhanced framework now comprises six stages: (1) data preparation, (2) pre-processing, (3) phrase-level aspect polarity extraction, (4) aspect extraction, (5) polarity aspect extraction, and (6) evaluation. This study also includes the development of four phrase-aspect polarity lexicons for MLPAPEL implementation, which adds to the research contributions. The proposed MLPAPEL coupled public lexicon ensembles with four phrase aspect polarity lexicons at the core of its four implemented processing layers. Experimental findings demonstrated the efficiency of MLPAPEL through the evidence of improved F1-scores and accuracy of all lexicons under test: SentiWordNet by +9.33% F1 and +5.10%, AFINN by +13.33% and +3.95%, TextBlob by +12.67% and +4.26%, VADER by +13.33% and +4.66%, and InSet by +9.33% and +5.29%. The method provides four main advantages: with phrase-level polarity detection, the extraction process is smoother, data dimensionality is reduced, and the process accelerates. However, though MLPAPEL is an important milestone in ABSA research, it inherits the following three limitations: domain specificity to student feedback analysis only, covering only the predefined aspects of interest, and handling a maximum of five-word phrases only. Moreover, developing the lexicons by hand poses scalability challenges. In addition, future research could be focused on reducing these limitations through semi-automated methods of lexicon expansion and enhancing the interpretation of implicit meanings of phrases to further improve their adaptability to changing patterns in the data.

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