

A Systematic Literature Review of Deep Learning Approaches in Image Processing: A Systematic Analysis in the Context of BISINDO

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Abstract

This research employs a Systematic Literature Review (SLR) to investigate the use of deep learning techniques in BISINDO (Bahasa Isyarat Indonesia) image recognition, crucial for improving communication accessibility for the hearing-impaired. The SLR consists of three stages: planning, conducting, and reporting. In the planning stage, research topics, questions, and search criteria are defined. The conducting stage involves thorough article retrieval and filtering. In the reporting stage, the study emphasizes various deep learning methods, such as Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), and a combination of both, each with distinct advantages and limitations. The paper also aims to identify research gaps and guide future deep learning model development. Additionally, it outlines the creation of a high-performance model, focusing on phases like image augmentation, data preprocessing, and model optimization. These efforts contribute to a better understanding of BISINDO image recognition, offering insights for researchers and practitioners working on advanced deep learning approaches to support easier communication for the hearing-impaired community.

Keywords : BISINDO, CNN, Deep Learning, LSTM, Systematic Literature Review

A. Introduction

Communication is an important thing that contributes to the survival of humans [1]. It helps people in expressing themselves and understanding other people's goals. This is also in line with human nature as social creatures who need other people and communication. Likewise with people with disabilities who require special attention to hearing or what are commonly referred to as deaf. In Indonesia, there are 2,615,000 people with hearing disabilities [2]. Along with that, sign language serves as a strong basis for effective communication in the deaf community and also supports their social inclusion. The two sign languages that are developed and used are SIBI (Sistem Isyarat Bahasa Indonesia) and BISINDO (Bahasa Isyarat Indonesia).

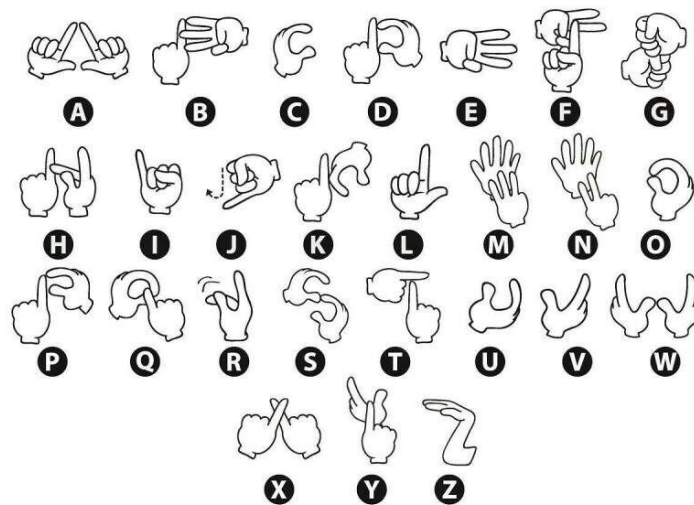


Figure 1. BISINDO Alphabetic [3]

SIBI is a visual medium commonly used by deaf people to communicate with the wider community. SIBI is a sign language that has been officially recognized by the Indonesian government and is used in teaching at Sekolah Luar Biasa (SLB) [4]. However, SIBI is considered more difficult as it observes the prefixes and suffixes of a word. Another difference with BISINDO is that SIBI is delivered using only one hand. On the other hand, BISINDO is a mother language that grows naturally in the Indonesian deaf community, the difference is shown in figure 1 and figure 2. BISINDO is a language that is easier in terms of use and understanding. Therefore, it is a more preferred language as it is considered more optimal, effective and expressive [5]. BISINDO plays an important role in facilitating communication and social integration for deaf people in Indonesia. This language, which is conveyed through hand gestures and facial expressions, has developed over time based on cultural influences and regional factors. This shows BISINDO's flexibility in adapting to diverse communication needs and contexts.



Figure 2. SIBI Alphabetic [3]

Good communication is achieved when the recipient and sender of the language both understand the message being expressed [6]. The challenge currently being faced by Indonesia is equal access and understanding of sign language among its people. Problems can arise when deaf people feel frustrated and isolated without having mediators around them which results in barriers to communication [7]. This needs to be addressed considering that every individual without exception has the right to express themselves through communication. In this era, almost everything depends on technology. One example is how technology has become the main supporting medium for communication. Unfortunately, there are no adequate communication facilities for the deaf community who use BISINDO as their main language. Therefore, the implementation of machine learning and deep learning algorithms can give a big impact through image recognition technology that can recognize BISINDO. Implementation of this model can help increase the sense of deaf people's inclusivity in modern society and achieve equality in communication for all individuals.

Understanding BISINDO remains limited in Indonesia, posing a significant challenge for effective communication among deaf individuals. Addressing this issue calls for the development of a BISINDO recognition system, which can be facilitated through the utilization and enhancement of deep learning algorithms. While several prior studies have explored this area, achieving satisfactory accuracy values has proven challenging. Conversely, in the domain of image recognition, the combination of two algorithms has demonstrated success in attaining high accuracy levels. This study seeks to contribute by serving as a guiding resource for future research endeavors. The ultimate aim is to amplify the awareness and acceptance of BISINDO in Indonesia. Through the comprehensive analysis and evaluation of various model developments and the application of deep learning algorithms within the realm of BISINDO, this research

aims to pave the way for enhanced socialization efforts and improved communication accessibility for the deaf community in the country.

B. Research Method

This research delves into the realm of applying deep learning algorithms to BISINDO image recognition. To navigate this exploration comprehensively, the chosen research methodology is the Systematic Literature Review (SLR) [8]. Renowned for its ability to systematically identify, evaluate, consolidate, and summarize relevant studies, SLR employs the PRISMA protocol (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). This protocol, known for enhancing the structure, comprehensiveness, and rigor of review reports, was officially registered on August 14, 2021, in the International Platform of Registered Systematic Review and Meta-Analysis Protocols (INPLASY)[11].

The guiding pillars of this study are encapsulated in four research questions: (RQ1) What are the commonly used algorithms for image recognition? (RQ2) What are the prevalent deep learning methods in BISINDO recognition? (RQ3) What steps can be taken to enhance the performance of deep learning models? (RQ4) How can high-performance models be developed in the context of BISINDO recognition? The intricate review process unfolds in three distinct yet interconnected stages [13]: planning, conducting, and reporting. The planning stage marks the inception of the SLR journey, where researchers meticulously define specific research questions or objectives that hone in on the unique facets of the study's focus. Simultaneously, inclusion and exclusion criteria are established, serving as the benchmarks that articles must meet for inclusion in the review. In this instance, the study casts its net over research spanning from 2019 to 2023, utilizing specific keywords like "BISINDO recognition," "deep learning," and "image recognition." The identification procedures executed, notably through the tool named Publish or Perish (POP), play a pivotal role in ensuring the inclusion of articles most relevant to the review. The conducting stage embodies the execution phase of the SLR. It involves a meticulous dance of article retrieval, screening, selection, and data extraction. Researchers embark on the task of amassing a substantial corpus of articles aligned with the study's focus. The subsequent screening process entails a thorough examination of titles and abstracts to ascertain whether articles meet the predefined inclusion criteria. Those articles that successfully navigate this screening stage proceed to the pivotal step of data extraction. Here, crucial data elements such as research methods, findings, and other pertinent information related to the research questions are meticulously gathered [14]. The reporting stage is the culmination of the SLR journey, where findings are systematically documented and presented. This phase encompasses the intricate processes of results and key findings analysis, the structured and systematic articulation of the review, concise summarization of the paper, and a candid acknowledgment of its limitations. Additionally, the researchers may proffer valuable recommendations for future research endeavors in this domain, underscoring the dynamic nature of BISINDO image recognition and the continuous need for refinement, innovation, and sustained research and development efforts to achieve optimal outcomes in the dynamic landscape of sign language interpretation through deep learning models.

C. Result and Discussion

Out of the all the collected articles, 15 met the established inclusion criteria. These selected articles underwent thorough extraction and analysis to address the predefined research questions (RQ1, RQ2, RQ3, and RQ4). The findings and insights gleaned from these 15 chosen articles are summarized in Table 1.

Table 1. Reference Comparison of Sign Language and Image Recognition

No	Title and References	Object	Algorithm	Research Result
1.	Indonesian Sign Language Image Detection Using Convolutional Neural Network (CNN) Method [7]	SIBI and BISINDO Alphabet	CNN	The recognition accuracy for SIBI sign language stands at an impressive 93.29%, highlighting the effectiveness of CNN in deciphering its complex signs. Nevertheless, there is potential for improvement, with a 9.1% margin for enhancement. In contrast, BISINDO, while maintaining a commendable performance, achieves an accuracy of 82.32%.
2.	Real-time BISINDO Hand Gesture Detection and Recognition with Deep Learning CNN [15]	BISINDO Alphabet	CNN	Utilizing Deep Learning Convolutional Neural Networks (CNN), real-time detection and recognition of BISINDO hand gestures yield a modest accuracy rate of 59.54%.
3.	Development of the Indonesian Sign Language (BISINDO) Translator Application using the Long-Short Term Memory Method [16]	BISINDO Alphabet	LSTM	Creating an Indonesian Sign Language (BISINDO) Translator Application with Long-Short Term Memory (LSTM) results in improved accuracy, reaching 85%.
4.	Android-Based Application for Real-Time Indonesian Sign Language Recognition Using Convolutional Neural Network [17]	BISINDO Alphabet	CNN	The CNN resulting in 75.38% at BISINDO dataset.
5.	A CNN-LSTM Approach to Human	Intelligent Signal Processing	CNN-LS TM	The amalgamation of CNN and LSTM methodologies yields enhanced result accuracy,

No	Title and References	Object	Algorithm	Research Result
	Activity Recognition [18]	Lab (iSPL) and University of California Irvine Human Activity Recognition (UCI HAR)		measuring at 99.06% for the iSPL dataset and 92.13% for the UCI dataset. The model's precision in discerning intricate patterns is further emphasized by minimal loss rates, registering at 3.92% for iSPL and 29.53% for UCI.
6.	A CNN-LSTM network with multi-level feature extraction-based approach for automated detection of coronavirus from CT scan and X-ray images [19]	SARS-CoV-2 CT Scan, SIRM Covid-19 CT Scan, and Chest CT Scan	CNN-LSTM	The combination of a CNN-LSTM network, using a multi-level feature extraction approach, works really well in automatically detecting coronavirus from different imaging datasets like SARS-CoV-2 CT Scan, SIRM Covid-19 CT Scan, and Chest CT Scan. The results show that the model performs strongly, achieving an impressive accuracy of 98.94% for SARS and 83.03% for SIRM. Also, the model is good at balancing true positives and false positives, as seen in its high precision, recall, and F1 score values for both datasets.
7.	Classification of benign and malignant subtypes of breast cancer histopathology imaging using hybrid CNN-LSTM based transfer learning [20]	Breast Cancer Histopathology Imaging	CNN-LSTM	Using a hybrid CNN-LSTM with transfer learning for classifying benign and malignant subtypes in breast cancer histopathology imaging has shown remarkable effectiveness, reaching an impressive accuracy of 99.75% and a recall rate of 99%.
8.	Development of CNN-LSTM combinational architecture for COVID-19 detection [21]	Chest CT Scan of Normal People and COVID-19 Infected	CNN-LSTM	An integrated CNN-LSTM architecture designed for COVID-19 detection, using Chest CT scans from both normal individuals and those with COVID-19, has produced highly promising outcomes.

No	Title and References	Object	Algorithm	Research Result
				The model achieves an accuracy of 98.91%, a precision of 100%, a recall of 97.82%, and an impressive F1 score of 98.90%.
9.	A novel CNN+LSTM classification model based on fashion-MNIST [22]	Fashion MNIST	CNN-LSTM	The CNN+LSTM classification model, when used with the Fashion-MNIST dataset, has proven to be notably effective, attaining an accuracy of 91.36%.
10.	A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images [23]	Chest CT Scan of Normal People and COVID-19 Infected	CNN-LSTM	A sophisticated CNN-LSTM network designed for detecting the novel coronavirus (COVID-19) from X-ray images has shown remarkable effectiveness, achieving an impressive accuracy of 99.2% and an F1 score of 98.9%.
11.	Recognition of offline handwritten Urdu characters using RNN and LSTM model [24]	Hand-written Urdu Characters	CNN-LSTM	When comparing RNN and LSTM, distinct results emerge: RNN achieves an accuracy of 73.62%, whereas LSTM demonstrates higher accuracy at 91.30%.
12.	Classification of Guava Fruit Ripeness Levels Based on Skin Color Using the Naïve Bayes Method [25]	Guava Image	Naïve Bayes	The Naive-Bayes on Image Recognition for Guava, resulting in 75% of accuracy.
13.	Establishment of a Recurrent Neural Network Model and Connectionist Temporal Classification in Offline Handwritten Word Recognition [26]	Hand-written Words	RNN and Connectionist Temporal Classification	The fusion of RNN and Connectionist Temporal Classification for the recognition of hand-written words yields an accuracy of 82.12%.
14.	Development of the SIBI Alphabet Sign Language Recognition Application Using the Convolutional Neural Network (CNN) Method [27]	SIBI Alphabet	CNN	SIBI, an Indonesian Sign Language, is classified using CNN, yielding an accuracy, precision, and recall of 80.76%.
15.	Implementation of the Convolutional Neural	Leaf Image	CNN	In another instance of image recognition using CNN for leaf

No	Title and References	Object	Algorithm	Research Result
	Network Method for Identifying Digital Images of Leaves [28]			images, the results show a 92% accuracy, 89% precision, 87% recall, and an F1 score of 88.51%.

The research mind map on deep learning approaches for BISINDO (Bahasa Isyarat Indonesia) image recognition encompasses a diverse set of objects, including BISINDO alphabet, SIBI alphabet, ISPL & UCI HAR datasets, Covi19 CT Scan images, and Handwritten Words. The investigation focuses on leveraging advanced techniques to effectively recognize and interpret these diverse visual elements that shown on figure 3.

Regarding the methodology, diverse deep learning techniques are investigated. Convolutional Neural Networks (CNN) are employed to capture spatial hierarchies and patterns within images, making them well-suited for tasks like recognizing alphabets and handwritten words. Long Short-Term Memory networks (LSTM) are utilized for their proficiency in modeling sequential dependencies, proving effective for datasets such as Covi19 CT Scans where both spatial and temporal aspects are critical. Additionally, the study explores combinations of CNN-LSTM and Recurrent Neural Networks (RNN) to leverage the strengths of both spatial and sequential processing. The research also delves into Naive Bayes, a probabilistic classifier, appreciated for its simplicity and efficiency, particularly in scenarios with limited computational resources.

The study evaluates different models using various metrics to understand how well they perform. Metrics like accuracy show how correct the model is, and loss functions measure the difference between predicted and actual values. Precision and recall metrics help understand the model's ability to avoid false positives and false negatives. The F1 score combines precision and recall to give an overall performance measure. This research aims to contribute to the improvement of deep learning in sign language and image understanding, focusing on challenges in datasets like BISINDO, SIBI, ISPL & UCI HAR, Covi19 CT Scans, and Handwritten Words. By using various objects, advanced methods, and thorough metrics, the study explores deep learning in the context of BISINDO image recognition. In the field of Sign Language Recognition (SLR), image recognition and deep learning methods have grown due to the need for accurate communication systems. This study explores important questions to understand image recognition algorithms and their use in BISINDO (Bahasa Isyarat Indonesia) recognition. The first question looks at common algorithms in image recognition. The second question focuses on prevalent deep learning methods for BISINDO recognition, considering the unique challenges of sign language. The third question examines steps to improve deep learning models in this area. Lastly, the fourth question explores strategies for building high-performance models for BISINDO recognition. Through these questions, this study aims to provide insights and a deeper understanding of the current state and future directions in the intersection of image recognition, deep learning, and BISINDO recognition.

(RQ1) What are the common-used algorithms for image recognition?

From the literature review, we found several algorithms suitable for image recognition. These include Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), a mix of CNN and LSTM (CNN-LSTM), Recurrent Neural Networks (RNN), and Naïve Bayes. These algorithms are popular choices in image recognition because they've shown effectiveness in various studies. The literature also emphasizes the importance of choosing the right algorithm based on the specific needs of the application and the nature of the image data. Factors like how complex the processing is, the dataset size, and the available computational resources should be considered when selecting an algorithm. This approach helps researchers and practitioners tailor their image recognition solutions to match their project's unique requirements, ensuring optimal results and performance in different applications.

(RQ2) What are the prevalent deep learning methods used in BISINDO recognition?

When creating a BISINDO image recognition model, you have a few deep learning options. Convolutional Neural Network (CNN) is a well-known and reliable choice for image recognition. Many previous studies have used CNN as their go-to algorithm. Another option is Long Short-Term Memory (LSTM), and there's also a combined method called CNN-LSTM. This combo uses CNN to extract features and LSTM to predict and classify time series data. Based on previous studies, CNN-LSTM often performs better than other models, according to the evaluation metrics used. A typical CNN has different layers like convolutional layers, pooling layers, a fully-connected layer, and an output layer. In the convolutional layer, filters or kernels are used to find patterns, like edges or textures, in the input data. This process is usually assisted by the ReLU activation function. Next is the pooling layer, which helps reduce the dimensions of the feature representation produced by the convolutional layer and prevents overfitting. Then comes the fully connected layer, with interconnected neurons that make final decisions or classify results. This layer also flattens the data from 3D to 1D.

(RQ3) What steps should be done to enhance the performance of the deep learning models?

The experiments were done multiple times, each with different scenarios, to find the best-performing model. Some studies used the same model on different datasets and got different results in the evaluation metrics. There are various reasons for this, like not doing proper image preprocessing, which can make the data quality poor. Noise in pictures can be a problem for the learning model, causing issues like reduced robustness and longer training time. Using the model to predict BISINDO's alphabets can be tricky because some letters look very similar if the model didn't learn well from the training data. Difficult letters include B, D, J, K, and P. The dataset's size matters too. A larger dataset helps the model learn better because it exposes the model to a wider range of examples. This diversity is important because it lets the model see different scenarios and patterns in the data. A larger dataset helps the model distinguish between different classes better and makes it less likely to make mistakes. It also helps the model adapt to new, unseen data in real-world situations and reduces the risk of overfitting. When

evaluating deep learning models, cross-validation with different folds is important for a robust assessment. But in some cases, randomized data separation is done instead of cross-validation due to reasons like computational complexities, limited resources, and time constraints. Cross-validation involves training and evaluating the model multiple times, which can be impractical if there aren't enough resources.

(RQ4) How can high-performance models be developed in the context of BISINDO recognition?

Many past studies on BISINDO used either CNN or LSTM but found that these models didn't perform well in BISINDO recognition. On the flip side, studies with different focuses used a combined algorithm (CNN-LSTM) and showed that it could create a predictive model with outstanding performance. One reason for this success is that CNN-LSTM combines spatial and temporal aspects of data, allowing it to recognize complex patterns and relationships. CNN can learn features from low to high levels in data, while LSTM can capture dependencies and relationships over time, making predictions more accurate. So, combining these two algorithms gives the best of both worlds. Another way to improve BISINDO recognition is to enhance the dataset. This means considering different lighting conditions, angles, and including various gestures beyond just alphabets. Better lighting conditions make the model more robust, helping it learn patterns even when lighting changes. This is crucial for real-world situations where lighting can be unpredictable. Varying camera angles can improve object recognition in models. Lastly, expanding the range of recognized gestures makes the BISINDO system more versatile. This enhances the user experience, especially for the hearing-impaired community, allowing for more natural and richer interaction or communication.

D. Conclusion

In summary, the systematic literature review (SLR) aims to provide insights into the development of image classification models for BISINDO recognition. After analyzing 15 articles, three commonly used algorithms are CNN, LSTM, and CNN-LSTM in image recognition. Furthermore, the combination of CNN-LSTM and improvements in the dataset, considering lighting conditions, various angles, and diverse gestures, prove beneficial in enhancing predictive model performance. This approach supports generalization, reduces bias, and exposes the model to a broader range of image scenarios, promoting accuracy. However, it's crucial to recognize that BISINDO, or Indonesian Sign Language, still encounters challenges that require continuous refinement efforts. Both the model and dataset necessitate ongoing attention and improvement to ensure more accurate and reliable results. Acknowledging the dynamic nature of BISINDO image recognition serves as a call to action, underscoring the significance of sustained research and development to achieve superior outcomes in the ever-changing landscape of sign language interpretation through deep learning models.

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Consent Form

A handwritten signature in black ink, appearing to read 'Jurgen' with a stylized flourish at the end.

Jurgen Loa

A handwritten signature in black ink, appearing to read 'Vincent' with a long, sweeping flourish extending to the right.

Vincent Budiman

A handwritten signature in black ink, appearing to read 'Richard' with a stylized flourish at the end.

Richard Dammara