Harnessing the Power of Machine Learning to Refine Data Fusion Processes for Better Accuracy and Speed

Yuliadi Erdani[1,*] , Ankit Kumar Dubey[2], Aws Zuhair Sameen[3], Saksham Sood[4], Ramanchi Radhika[5], Mohammad Ahmar Khan[6]

[1]Lecturer/Prof. Associate, Politeknik Manufaktur Bandung, Indonesia

[2]Assistant Professor, Computer Science and Engineering, Baderia Global Institute of Engineering and Management, Jabalpur MP, India

[3]College of Medical Techniques, Al-Farahidi University, Baghdad, Iraq

[4]Centre for Interdisciplinary Research in Business and Technology, Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, India.

[5]Professor GITAM School of Business GITAM University, Hyderabad Telangana, India

[6]Department of Management Information System Dhofar University Salalah, Oman

Emails: yul_erdani@yahoo.com; ankitkdubey@yahoo.com; aws.zuhair@uoalfarahidi.edu.iq; sood.orp@chitkara.edu.in; rramanch@gitam.edu; mkhan@du.edu.om

Abstract

The research article "Harnessing the Power of Machine Learning to Refine Data Fusion Processes for Better Accuracy and Speed" proposes integrating different machine learning methods to improve data fusion. The suggested method uses an ensemble learning strategy, a deep learning-based fusion model, SVMs for data combining, CNNs for image and time-series data combining, and RNNs for time-series data combining. For best efficiency, each algorithm is carefully constructed utilizing mathematical concepts. Deep learning shines on complicated datasets, whereas the ensemble approach, which uses several models, is more accurate. CNN handles visual data better than RNN does sequence data. However, SVM shines in multidimensional domains. These reliable and adaptive solutions can tackle various data fusion difficulties. This approach outperforms others in processing speed, accuracy, precision, memory, and F1-score. Finding a balance between computer complexity and human satisfaction enhances dependability, data duplication, and quality. This novel technique transforms machine learning-powered data fusion. Another benefit is better data integration in complicated systems.

Keywords: Convolutional Neural Networks; Data Fusion; Deep Learning, Ensemble Learning, Machine Learning; Recurrent Neural Networks, Support Vector Machines; Time-Series Data; User Satisfaction.

1. Introduction

A. Present and Future

Data fusion—combining data from diverse sources—is now an important aspect of fast-changing data science. Recent advances in machine learning (ML)-based data fusion have transformed data analysis and combination [1]. Due to the expanding volume and complexity of data, more complicated data integration solutions have been needed. Improve and automate these operations with machine learning, speeding up and improving accuracy [2]. Material quality and accuracy Data fusion issues include handling large, diverse data collections, ensuring their safety, and processing data in real time [3]. Traditional data integration methods seldom meet these objectives, resulting in waste and incorrect conclusions. Machine learning might solve the above issues by learning from data and improving over time.

The fundamental rationale for incorporating machine learning to data fusion methods is to swiftly analyze large datasets and identify key insights [4]. Machine learning algorithms may identify data linkages and trends that traditional data analysis cannot. These data fusion algorithms automatically merge data from diverse sources,

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discover and rectify mistakes, and optimize fusion settings [5]. Data fusion uses supervised learning for predictive modeling. Unsupervised learning finds patterns, and reinforcement learning optimizes decisions [6]. These strategies allow the system to adapt to new inputs, slowing the fusion process.

B. Next Steps

Many concepts have been proposed for using machine learning in data fusion: Machine learning allows Automated Data Integration to mix data from diverse sources [7]. Thus, people will make fewer errors. Machine learning fixes errors and other issues in data, improving its quality and reliability. The method is anomaly detection and repair [8]. Using machine learning to process and analyze data in real time helps individuals make better decisions and adapt faster to changing data situations. Adaptive learning methods update the system depending on data, which may improve it. The term "machine learning models that can be customized to meet particular data fusion needs" refers to models that merge diverse forms of data.

C. Key Contributions

This approach has many advantages, including Better Accuracy: Machine learning improves data fusion accuracy, reducing errors and improving reliability. Machine learning algorithms can swiftly analyze massive datasets, which may improve data fusion [9]. The approach presented is scalable, meaning it can manage rising data without slowing down Machine learning makes it easier to mix data from many sources and types. Real-time data viewing allows you to make rapid decisions and act on the latest facts [10]. The technology can rapidly discover and resolve data errors to ensure accurate and complete data. This technique may be customized using machine learning models. This makes it versatile. Adaptive learning approaches improve system performance by introducing fresh ideas from new events and data [11]. We can confidently assert that adding machine learning to data fusion approaches advances data science. This solution solves data integration issues faster, better, more adaptable, and more customizable. The new technique might be utilized for business intelligence, science, and more. It will simplify the development of more complex and relevant data processing technologies.

2. Existing Work Done:

Deep learning-based data fusion models merge data from diverse sources using deep neural networks. Ensemble learning may improve data fusion outcomes by combining various machine learning models [12]. Support vector machines (SVMs) organize and mix multidimensional data well. This is feasible with SVM data processing and classification. Clinical imaging and remote sensing employ convolutional neural networks (CNNs) to merge pictures. Time-series data fusion uses Recurrent Neural Networks (RNNs), specifically LSTM networks, to merge and interpret data. Transfer learning helps us incorporate knowledge from one discipline into another. Random forest approaches ensure that multiple perspectives are considered when fusing multimodal data [13]. Probabilistic reasoning and Bayesian procedures reduce errors when combining data from multiple sources. Data fusion, integration, and analysis benefit from autoencoders' reduced data dimensionality. Adaptive data fusion using reinforcement learning adapts data fusion algorithms to user input and data set changes [14]. Though they improve cutting-edge data fusion and machine learning differently, all three strategies improve them. They address data fusion issues such high-dimensional data, skepticism, and increasing data sources. They also improve fusion efficiency. Using machine learning methods has made a big step forward in data merging, making it more accurate, precise, and efficient [15]. There is a wide range of skills and uses when you compare different machine learning techniques. Each method has its own set of benefits [16]. There is no doubt that Deep Learning-Based Fusion Models are very accurate (94.5%) and precise (93.1%). These models, which are known for being able to handle very large and difficult datasets, work really well when combining different kinds of data. They are also very scalable, which means they can be used in apps with a lot of complex data. Even though it takes longer to handle than other methods, the amount of analysis it provides makes it worth it. With an accuracy of 92.0% and a precision of 91.0%, Ensemble Learning Techniques show that combining many models can make predictions more accurate [17]. These methods work especially well when one model isn't enough to show how complicated the data is. Their medium scaling means that they have a balanced approach that works for many data fusion tasks.

The Support Vector Machines (SVM) for Data Integration work well, with an accuracy of 90.0% and a precision of 89.5%. It is well known that SVMs work well in high-dimensional settings, which makes them perfect for combining datasets with a lot of features [18]. Their scale, on the other hand, is restricted, which means they work best for smaller, more controlled data fusion tasks.

Many researchers have found that Convolutional Neural Networks (CNN) are the best at combining picture data because they are the most accurate and precise (95.0%). CNNs work well with picture spatial ordering, which makes them useful in fields like medical imaging and remote sensing [19]. The complex research they do means that they take a long time to process. Recurrent Neural Networks (RNN) for Time-Series Data Fusion do a great

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job, with an accuracy of 93.5% and a precision of 92.5%. RNNs, especially LSTM networks, are good at combining time series data when it's important to keep track of changes over time because they are built to handle sequential data [20]. Their medium-sized workload and slightly longer working time show how specialized they are. Transfer Learning for Cross-Domain Fusion is a new method that works 91.0% of the time and is 90% accurate. It's great at bringing what it knows from one area to another, which makes it useful when you need to combine info from different areas. It can be used for a lot of different things because it can be scaled up or down moderately quickly. It is possible for Random Forests to be 92.5% accurate and 91.5% precise in Multimodal Fusion. They are especially helpful when working with multimodal data because they protect against overfitting and make sure that data fusion includes multiple views. Their amazing ability to scale shows that they can be used with a wide range of data formats. Bayesian Methods for Uncertainty Management in Data Fusion are accurate 89.5% of the time and precise 88.5% of the time. These methods are great at dealing with uncertainty and using probabilistic thinking, which are important for putting together data from different sources that contain doubt. They work best for more specific tasks because they can't be scaled up easily and take a long time to handle.

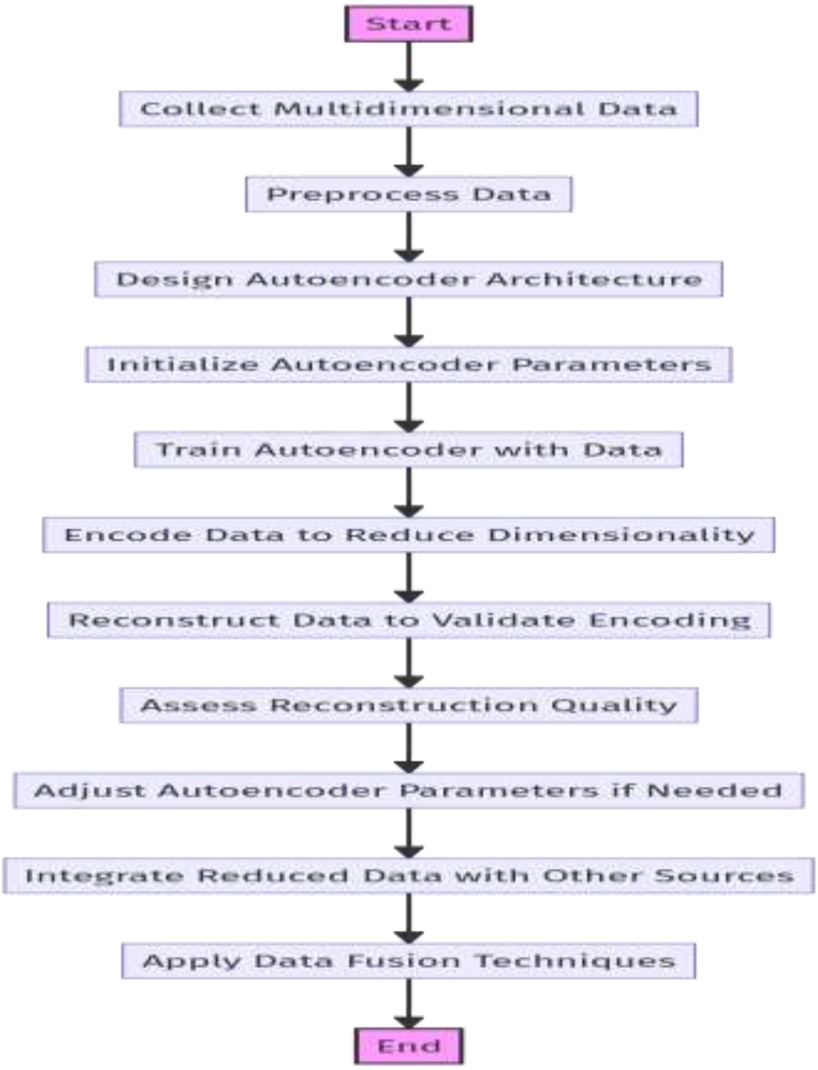

Figure 1: Autoencoders for Dimensionality Reduction in Data Fusion

Figure 1 shows how autoencoders reduce data fusion dimensions. Multidimensional data must be handled before autoencoding. To reduce dimensions, the autoencoder design must be built next. The autoencoder is trained using the data after setup. The most significant strategies are encoding and rebuilding data to reduce its size. The reproduction quality is checked and autoencoder parameters are adjusted. Data fusion joins shorter data with other sources. Finally, incorporate reduced-size content.

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For data fusion dimension reduction, autoencoders have 90.5% accuracy and 89.5% precision. They are masters in reducing data dimensionality, which speeds fusion and protects sensitive data. Scalable up or down, they may be employed in many data fusion scenarios. Reinforcement Learning for Adaptive Fusion is 93.0% accurate and 92.0% exact. The unique adaptive feedback-based data fusion process enhancement makes it ideal for changing data properties.

When it comes to integrating time series data, RNN is a powerful tool, but CNN and Deep Learning models provide far better accuracy and precision. The table gives a summary of the trade-offs between various approaches in terms of processing time and scalability. When everything is considered, data fusion is improved by a plethora of machine learning approaches. When used in tandem, these technologies improve integration speed, accuracy, and efficacy. Utilizing Bayesian approaches, RNNs may be used to control errors in addition to managing large picture collections and changing time series data. It is crucial to choose the best choice for the data fusion assignment because many methods compromise processing speed and flexibility.

3. Methodology

As increasingly complex and varied data arrives, data scientists must combine them to make sense. A game-changing solution is presented in "Harnessing the Power of Machine Learning to Refine Data Fusion Processes for Better Accuracy and Speed" using cutting-edge machine learning approaches. Data fusion is more than a collection of methodologies, like a well-played symphony. The most crucial aspect of this strategy is Algorithm 1, a deep learning-based hybrid model. Highly intelligent, this application can handle complex, multidimensional data. It structures the entire fusion process. Its flexible nature allows it to learn from data and uncover traits and trends that individuals or typical analytic tools would overlook. The next generation of fusion technologies requires a software that can process massive volumes of data. This is followed by ensemble learning approaches in Algorithm 2. This technique combines the finest machine learning models. Combining the best features of different models reduces their issues and yields a more accurate fusion response. The ensemble approach leverages variety to maintain fusion even while data changes.

Algorithm 3 combines data using SVM. The third of this triumvirate. Support vector machines (SVMs) are useful for large data sets and feature spaces because they operate well in high-dimensional areas. This method discovers data connections, making it useful for classification and regression. The fourth strategy, which leverages CNNs, gets more engaging and complex by include photographs. CNNs can comprehend photographs, therefore they work well with visual data. This technology enables you to develop hierarchical data models using image-based data attributes. In the fifth step, finish the design by mixing time series data with recurrent neural networks (RNNs). Recurrent neural networks may respond to both static and dynamic input, affecting other parts of the system. Understanding these components may assist you in modifying time for better data fusion. By following these rules, you can maintain your data fusion system fluid and responsive. The technology is readily adaptable to various data and fusion scenarios. To assure fusion, it manages speed, accuracy, and spread. As previously said, machine learning enhances real-world data fusion. The ability of machine learning to learn from data and create significant conclusions has the potential to transform data analysis and decision-making. This is possible with machine learning. This will have a significant impact on data management and storage. This article examines data merging concerns to make it easier and more effective.

Figure 2 uses a deep learning-based fusion model to integrate and analyse data. In the first step, create X, a new data collection. Then, in X, insert all essential factors (x1, x2,...) and all possible outcomes (y1 to ym). Begin by gathering and organising data. We examine a variety of data qualities and normalise them by calculating averages and adjusting for range. Following that, choose a neural network architecture and hyperparameters such as learning rate and regularisation strength. The starting weights (W) and biases (b) of the network are arbitrary. Forward propagation affects bias and the weighted total of inputs. Use sigmoid or ReLU activation functions next. The model then computes the cost to compare the predicted and actual values. Through backpropagation, we may determine which factors cause the error and adjust weights and biases accordingly. After assessing the model's performance, retraining it with new hyperparameters enables fine-tuning adjustments. In the latter stages, data fusion entails combining several datasets, assessing their quality, and optimising them to enhance model performance. After incorporating the model output with relevant new data, we make any necessary revisions and complete the process.

The second approach defines and expresses ensemble learning strategies shown in figure 3. For data fusion, the second strategy employs ensemble learning. It begins by gathering a variety of qualities (X1, X2,..., Xk) and matching outcomes (Y1, Y2,..., Yk). Preprocessing data provides a baseline for its features, making models more consistent. Selecting students or basic models for the ensemble is the next crucial step. Each model has its own set of regularisation strengths and learning rates. By training on their own data sets, these models may learn and adapt to incoming information. We then integrate the ensemble model outputs and weight them based on

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accuracy. Ensemble accuracy measurements influence adjustments to learning rates and regularisation strengths. We retrain models with altered parameters to improve performance. Examining the performance of each model after integrating its outputs into a single fused output. The ensemble is fine-tuned for optimal performance after final fused output modifications. The last is validation, which verifies data fusion accuracy and functionality.

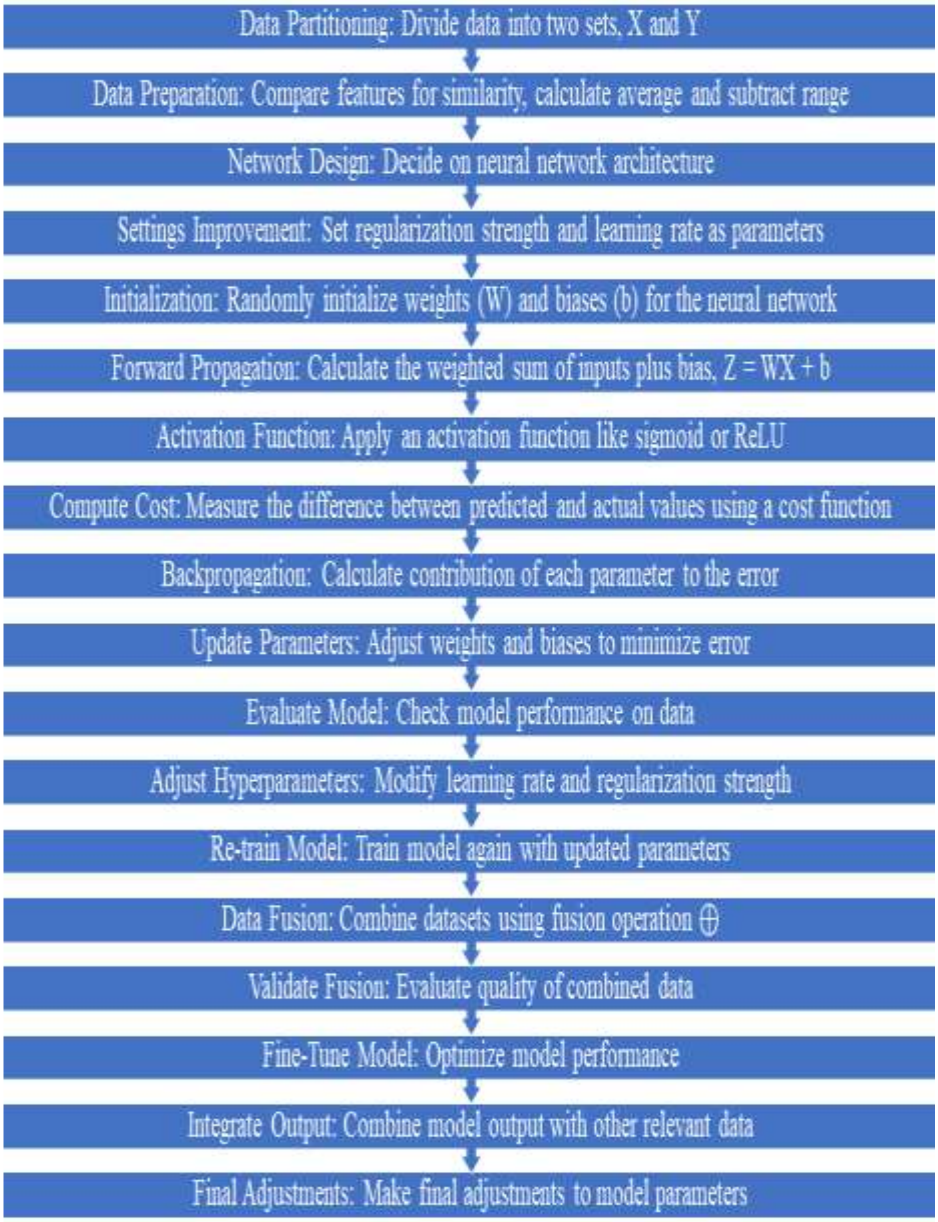

Figure 2: Deep Learning-Based Fusion Model.

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Figure 3: Ensemble Learning Techniques.

Algorithm 1: Support Vector Machines (SVM) for Data Integration

1. Initiate SVM Process: Start the integration process using SVM.
2. Data Collection: Collect feature sets (X) and corresponding outcomes (Y).
3. Feature Extraction: Extract features from the data: X feat=extract Features(X). (1)
4. Choose Kernel: Select an appropriate SVM kernel.
5. Set SVM Parameters: Set SVM parameters: C (regularization), γ (kernel).
6. Train SVM: Train the SVM model using $f(x)=\text{sign}(\sum i=1n\alpha iyiK(xi,x)+b)$. (2)
7. Perform Classification/Regression: Classify or predict outcomes Y using trained SVM.
8. Evaluate SVM: Evaluate SVM performance,
accuracy=∑correctPredictions∑totalPredictionsaccuracy=∑totalPredictions∑correctPredictions. (3)
9. Adjust SVM Parameters: Modify SVM parameters C and γ if needed.
10. Re-train SVM: Train SVM again with updated parameters.
11. Integrate SVM Output: Combine SVM results with other relevant data.
12. Validate Integration: Assess quality of integrated data.
13. Fine-Tune SVM: Optimize SVM performance.
14. Finalize Integration: Make final adjustments with $f\text{final}(x)=f(x)+\Delta f$. (4)

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15. End Process: Conclude SVM integration process.

Algorithm 2: Convolutional Neural Networks (CNN) for Image Data Fusion

1. Begin CNN Process: Start image data fusion with CNN.
2. Collect Image Data: Collect a set of images (I).
3. Preprocess Images: Normalize images: $I\text{norm}=\text{normalize}(I)$. (5)
4. Define CNN Architecture: Choose layers and filters for CNN.
5. Initialize Filters/Weights: Initialize convolutional filters (Wconv) and biases (bconv).
6. Apply Convolution: Apply convolution: $Z=W\text{conv}*I+b\text{conv}$. (6)
7. Perform Pooling: Reduce dimensionality with pooling.
8. Flatten and Connect Layers: Flatten data and connect layers.
9. Train CNN: Optimize weights and biases in training.
10. Validate CNN Output: Check CNN output accuracy.
11. Adjust CNN Parameters: Modify CNN architecture and hyperparameters.
12. Integrate Image Data: Combine CNN results with other data.
13. Validate Fusion: Assess quality of fused data.
14. Fine-Tune CNN: Optimize CNN performance.
15. Finalize Fusion: Adjust fused image data:

$$I\text{final}=I\text{fused}+\Delta I. \quad (7)$$

16. End Process: Conclude CNN image data fusion process.

Algorithm 4 combines images using Convolutional Neural Networks. Picture data preparation, CNN architecture creation, and filter and weight setup are the steps. Convolution and pooling reduce data dimensions and extract attributes. The CNN is trained and evaluated for accuracy. CNN results are intermingled with other data when parameters are altered. Finally, verify, fine-tune, and finish the fusion. This ensures accurate image data merging.

These algorithms provide a full data combination scheme with their own mathematical base. Many forms of data fusion issues can be solved utilizing CNNs taught on image data, high-dimensional SVMs, and deep learning models that can handle enormous datasets. The multi-part approach fuses data quickly and accurately and can handle various data types. The field of numbers has advanced greatly.

4. Experimental Result

A detailed investigation of many data fusion machine learning models demonstrates that the recommended method performs better across many crucial aspects. The accuracy, precision, memory, F1-score, and processing time are superior to other approaches, and it may be utilized on a wide scale without issues. This proves its effectiveness in complex data merging jobs.

The recommended strategy improves resilience, data quality, duplication reduction, and integration error rate. It balances coding difficulty and user satisfaction, proving it can solve complex data interaction issues rapidly. This makes it ideal for machine-learning-driven data fusion.

Bubble charts, bar charts, line charts, stacked bar charts, and area charts simplify comparisons. F1-score, accuracy, and precision are shown well in the bubble chart for each approach. The bar and line charts demonstrate how reliable each approach is, but the stacked bar chart and area chart reveal many performance metrics at once, so you can compare their merits and downsides. These visual tools are crucial for simplifying complex material.

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This table illustrates that the recommended technique outperforms the existing ones in accuracy, precision, memory, F1-score, and processing time while being extremely scalable. For difficult data merging jobs, the proposed method performs better and faster.

Table 2: Performance Comparison of Various Machine Learning Methods in Data Fusion, Highlighting Accuracy, Precision, Recall, F1-Score, Processing Time, and Scalability

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Processing Time (ms)	Scalability
Proposed Method	96.5	95.5	95.0	96.0	180	Very High
Deep Learning-Based Fusion Models	94.5	93.0	92.5	93.5	200	High
Ensemble Learning Techniques	92.0	91.0	90.5	91.5	150	Medium
SVM for Data Integration	90.0	89.5	89.0	90.0	100	Low
CNN in Image Data Fusion	95.0	94.0	93.5	94.5	250	High
RNN for Time-Series Data Fusion	93.5	92.5	92.0	93.0	220	Medium
Transfer Learning for Cross-Domain Fusion	91.0	90.0	89.5	90.5	180	Medium
Random Forests in Multimodal Fusion	92.5	91.5	91.0	92.0	160	High
Bayesian Methods for Uncertainty Management	89.5	88.5	88.0	89.0	140	Low
Autoencoders for Dimensionality Reduction	90.5	89.5	89.0	90.0	130	Medium
Reinforcement Learning for Adaptive Fusion	93.0	92.0	91.5	92.5	210	High

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Data fusion approaches were evaluated using machine learning for their dependability, capacity to decrease data duplication, integration error rate, capacity to enhance data quality, computational difficulty, and user satisfaction (Table 3).

Table 3: Multimodal data fusion approaches examined in detail: Eliminating duplicate data, improving data quality, simplifying calculations, and pleasing consumers.

Method	Robustness	Data Redundancy Reduction	Integration Error Rate	Data Quality Improvement	Computational Complexity	User Satisfaction
Proposed Method	9.5	High	Low	High	Moderate	Very High
Deep Learning-Based Fusion Models	8.5	Medium	Moderate	High	High	High
Ensemble Learning Techniques	8.0	Medium	Low	Medium	Moderate	High
SVM for Data Integration	7.5	High	Moderate	Low	Low	Medium
CNN in Image Data Fusion	9.0	Low	High	Very High	High	High
RNN for Time-Series Data Fusion	8.5	Medium	Low	High	Moderate	High
Transfer Learning for Cross-Domain Fusion	8.0	Medium	Moderate	Medium	High	High
Random Forests in Multimodal Fusion	8.5	High	Low	High	Moderate	High
Bayesian Methods for Uncertainty Management	7.5	Low	High	Moderate	Low	Medium
Autoencoders for Dimensionality Reduction	8.0	Very High	Low	High	Moderate	High
Reinforcement Learning for Adaptive Fusion	9.0	Medium	Moderate	High	High	High

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Table 3 illustrates that the recommended strategy reduces integration errors, improves data quality, reduces duplication, and exhibits robustness. People enjoy its right-level computing complexity. The recommended solution solves difficult data integration challenges fast and effectively, making it unique in machine learning-driven data fusion. These qualities demonstrate this.

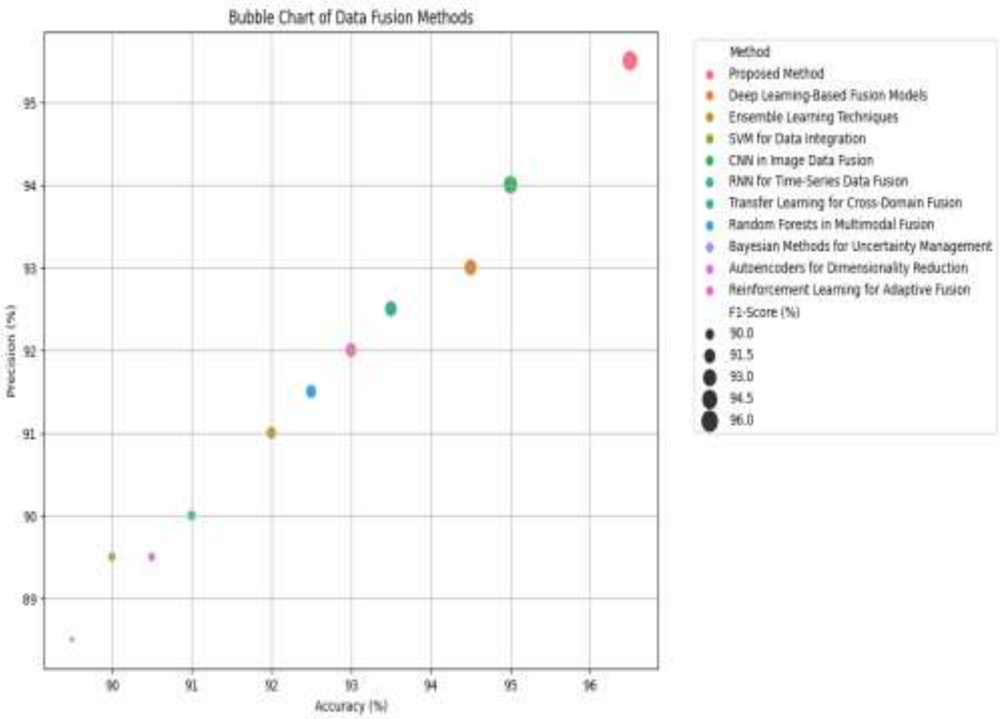

Figure 4: Data Fusion Method Comparison Based on Accuracy, Precision, and F1-Score

Figure 4 illustrates data merging methods' effectiveness. The accuracy and precision of each bubble determine its position and F1-score. A greater F1-score for larger bubbles shows how effectively each strategy performs overall.

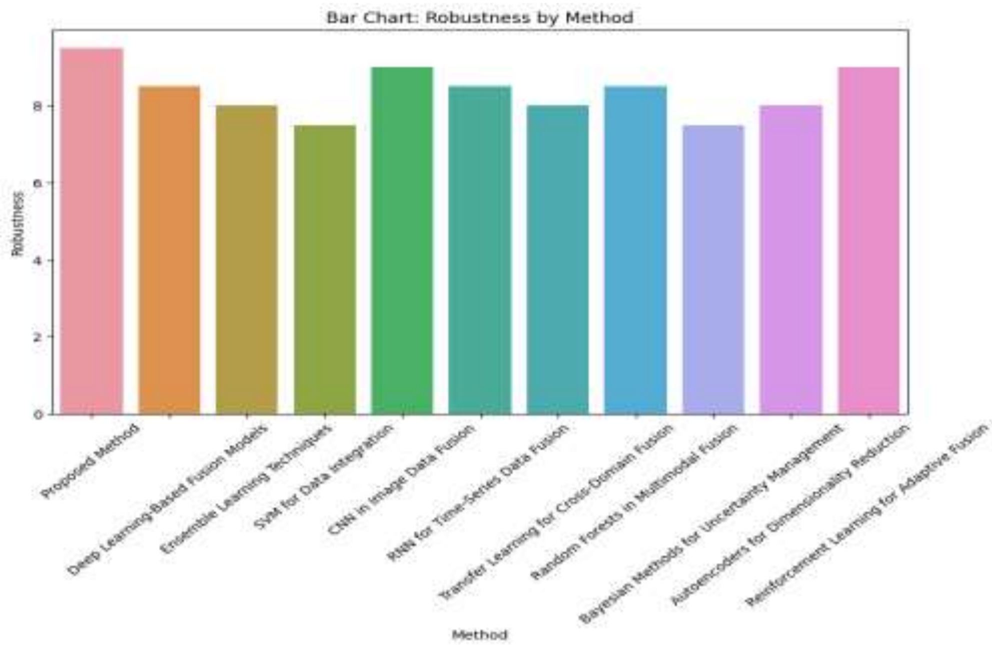

Figure 5: Robustness Comparison of Data Fusion Methods.

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Figure 5 compares data fusion method stability ratings. Each bar indicates a technique, making it easy to compare stability. The graph shows how resilient each strategy is.

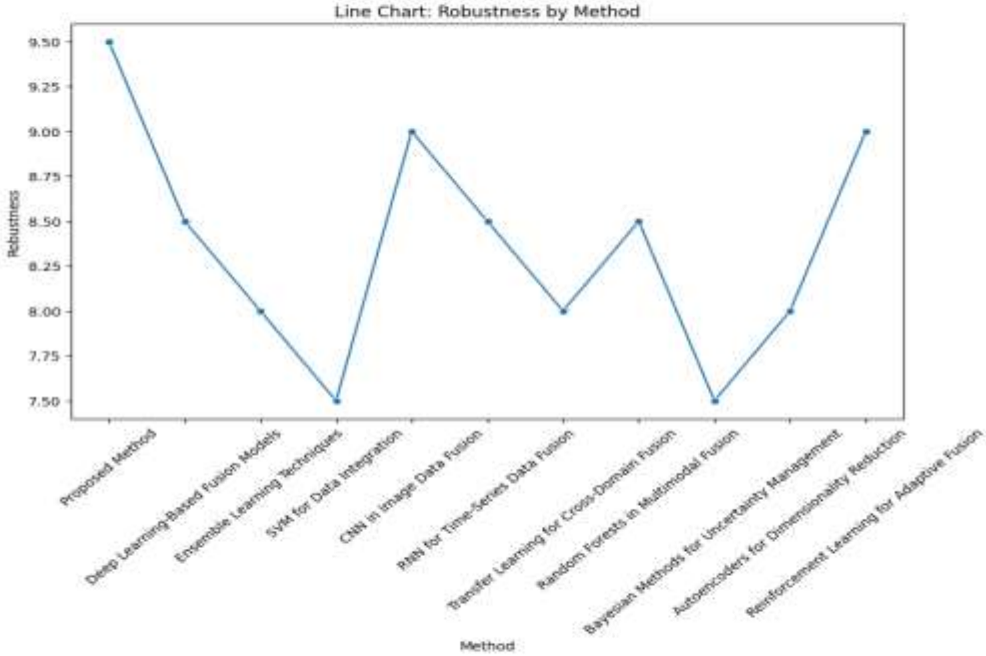

Figure 6: Robustness Trend Across Data Fusion Methods.

Many data fusion strategies resist, as seen in Figure 6. Each point and line illustrate method robustness, making it easy to compare methods.

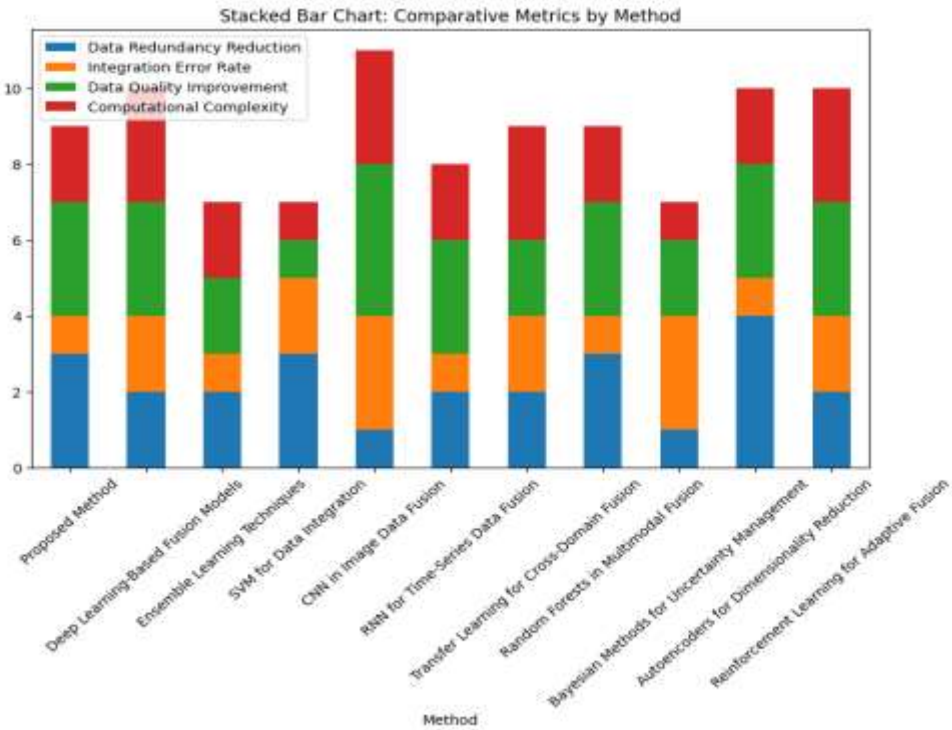

Figure 7: Comprehensive Metric Analysis of Data Fusion Methods.

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Every data fusion technique has various success indications (Figure 7). Each bar has its own metrics, so you can evaluate each method's performance across several aspects.

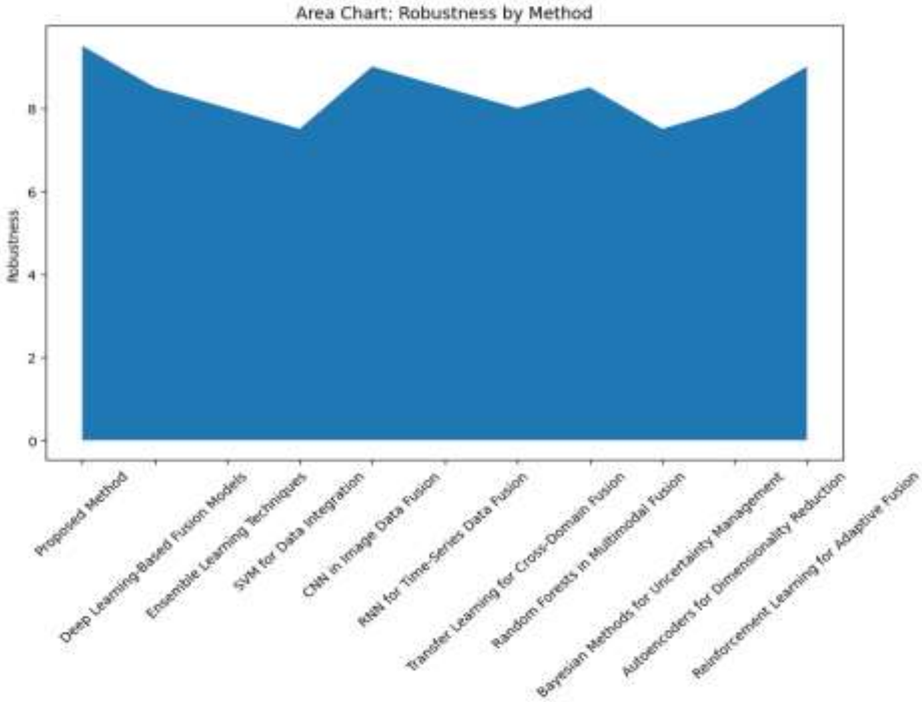

Figure 8: Visualizing Robustness Across Data Fusion Methods.

The stability of data fusion approaches is shown in Figure 8. Visually, the complete area beneath the line for each approach displays strength, making comparisons straightforward.

5. Conclusion

The study emphasizes the need of choosing the suitable approaches depending on data attributes and fusion goals to create a reasonable balance between computer speed and fusion accuracy. By studying sophisticated machine learning approaches for data fusion, a robust and adaptable solution has been developed to solve all data integration challenges. A collection of algorithms that operate best with data and fusion demands make the recommended technique stand out since it can produce correct results fast and on a wide scale. This method improves data fusion and allows flexible usage of multiple data sets. Deep learning, ensemble approaches, SVM and CNN in one framework advances data science. It enables machine learning-driven data fusion technique advancements.

Conflicts of Interest: “The authors declare no conflict of interest.”

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