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Development of Social Work Demand Forecasting System Integrating Deep Learning and IoT Technology

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ABSTRACT: The escalating demand for social work services, driven by global demographic shifts and socioeconomic challenges, underscores the necessity for innovative technological interventions to facilitate proactive service delivery. This research presents a comprehensive forecasting system for social work demand that integrates deep learning methodologies with Internet of Things (IoT) technology, aimed at enhancing both the efficiency and quality of services provided. The proposed system utilizes a hybrid model combining Convolutional Neural Networks (CNN) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for temporal data modelling, achieving a prediction accuracy of 94.8%, which represents a 30.8% enhancement over conventional forecasting methods. The IoT framework consists of 5,320 sensing points that gather multimodal data from various sources, including environmental monitoring, health tracking, and safety alert systems. Implementation of this system across 20 social work institutions yielded notable improvements: a reduction in response time from 8,500 milliseconds to 320 milliseconds, an increase in system availability to 99.2%, and a user satisfaction rate of 91.5%. The cost-benefit analysis indicates a payback period of 1.7 years, with anticipated net benefits of NT$35.26 million over five years. This study offers a replicable technical framework for the modernization of social work practices while addressing critical ethical considerations such as privacy protection, algorithmic bias, and the dynamics of human-machine collaboration. The findings contribute to the advancement of more equitable and effective social welfare systems through the application of technological innovations.

KEYWORDS: Deep Learning, Internet of Things (IoT), Social Work Demand Forecasting, CNN-LSTM Hybrid Model, Multimodal Data Fusion

I. INTRODUCTION

1.1 Research Background and Motivation

The global trend of population aging, coupled with shifts in social structures and the complexities of the economic landscape, has led to a marked increase in the demand for social work services. This demand is characterized by its diversification and rapid escalation. Traditional models of social work service delivery often depend on reactive demand response strategies, which are insufficient for proactive forecasting and early intervention. Consequently, these models contribute to challenges such as inefficient resource allocation and discrepancies between service supply and demand (Fatai et al., 2023; van den Broek et al., 2025). Furthermore, social workers are confronted with substantial caseloads and considerable time constraints, underscoring the necessity for technological interventions to improve service efficacy.

In recent years, advancements in artificial intelligence, particularly in deep learning technologies, have matured across various sectors, offering transformative potential for the field of social work. Deep learning possesses the capability to analyse extensive and complex datasets, discern underlying patterns, and generate accurate predictions. This functionality can significantly aid social workers in areas such as risk assessment, resource distribution, and service planning (Sciarretta et al., 2022; Yurttabir, 2025). Additionally, the rapid evolution of Internet of Things (IoT) technology has introduced unparalleled data collection and monitoring capabilities within social work. This technology facilitates real-time access to the living conditions, health metrics, and environmental contexts of service recipients through an array of smart sensors (Belani et al., 2025; Thewmorakot, 2025).

Statistical analyses regarding the demand for social work professionals in Taiwan reveal that, in 2023, the incidence of various social work cases increased by an average of 12.1% compared to 2022. Notably, the demand for mental health services surged by 13.5%, while the need for employment counselling rose by 13.6% (Lee et al., 2024). This persistent growth in service demand, in conjunction with constrained human resources, necessitates technological innovations aimed at enhancing both the efficiency and quality of social work services.

1.2 Literature Review and Research Gaps

1.2.1 Application of Deep Learning in Social Work

The exploration of deep learning technologies within the domain of social work is progressively gaining traction, with a primary emphasis on risk assessment, case prediction, and service optimization. The investigation conducted by Meindl and Wilkins (2025) assessed the predictive capabilities of social workers regarding future actions, events, and outcomes, revealing that the accuracy of conventional methodologies hovers around 72%, thereby indicating significant potential for enhancement. Recent investigations have demonstrated that employing a hybrid methodology that amalgamates support vector regression with deep learning models can markedly improve the accuracy of social function predictions, achieving levels exceeding 85% (Mumenin et al., 2025; Ren et al., 2025; Thakre et al., 2025).

The synergistic application of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks has exhibited commendable efficacy in mental health counselling systems, attaining an overall accuracy of 85.7%, a mean squared error of 0.041, and an F1 score of 85.2% (Ruchonnet-Métrailler et al., 2024; Zhao et al., 2025). This technological combination is particularly adept at managing sequential data and complex pattern recognition, thereby providing a robust technical foundation for forecasting social work requirements.

1.2.2 Development of the Internet of Things in Social Services

The integration of Internet of Things (IoT) technology within social services is becoming increasingly prevalent, primarily encompassing three domains: smart monitoring, environmental monitoring, and health management. These applications offer substantial technical support aimed at enhancing service quality, reducing operational expenditures, and improving user experiences.

A. Application of Smart Monitoring

Research conducted by the Local Government Association in the United Kingdom indicates that approximately 60% of local government expenditures are allocated to social care services, with the implementation of IoT devices emerging as a pivotal strategy to augment care efficiency and service quality (Melianova et al., 2024; Rehman et al., 2025). Remote monitoring systems enable vulnerable populations and the elderly to maintain independent living at home for extended periods, thereby diminishing reliance on institutional care and lowering overall care costs. These systems typically integrate wearable sensors, environmental sensors, and real-time communication technologies to continuously monitor users’ physiological conditions (e.g., heart rate, blood pressure, and body temperature) and living environments (e.g., indoor temperature and air quality), promptly notifying caregivers or family members in the event of abnormalities.

Fall detection sensors represent a critical component of smart monitoring systems. These devices can accurately identify fall incidents and automatically issue alerts, thereby reducing emergency response times and significantly mitigating the severe consequences associated with falls. Additionally, medication dispensing monitoring devices connected via IoT facilitate timely reminders for users to adhere to their medication schedules, thereby preventing health risks associated with missed or incorrect dosages.

B. The Role of Environmental Monitoring

The deployment of IoT technology in environmental monitoring enables real-time assessments of the safety and comfort of the environments inhabited by service users. By utilizing temperature and humidity sensors, air quality monitors, light sensors, and other devices, the system can evaluate the potential health impacts of environmental changes on users and provide recommendations for adjustments. For instance, for elderly individuals or chronic patients sensitive to respiratory conditions, the system can issue warnings when pollutant concentrations in the air exceed safe levels, prompting users to take protective measures.

Such environmental monitoring systems not only enhance the safety of home care but also furnish social workers with objective, real-time environmental data, thereby facilitating the formulation of more precise care plans and intervention strategies.

C. Integration of Health Management

The utilization of IoT devices in health management fosters continuous monitoring and analysis of personal health data. Wearable health trackers, smart mattresses, and non-contact physiological monitors can gather multidimensional data regarding users’ heart rates, blood pressure, sleep quality, and activity levels. This data can be integrated and analysed through cloud platforms, providing empirical evidence for social workers and healthcare teams to support case management and health promotion (Subbiah, 2025; Sultana et al., 2025).

This real-time and continuous health monitoring not only aids in the early identification of health risks but also encourages users to engage in self-management and adopt healthier behaviours, thereby enhancing their overall quality of life.

D. Benefits of IoT Technology

The aforementioned IoT applications have already made significant contributions to practical social work. Firstly, improvements in service quality are evident through more accurate demand identification and timely interventions, which collectively reduce the incidence of emergencies. Secondly, operational costs have been substantially diminished due to remote monitoring and automated management, thereby minimizing the wastage of manpower and time. Lastly, the user experience has been enhanced, as individuals can receive safety assurances and health management within familiar and comfortable environments, thereby increasing their autonomy and sense of dignity.

E. Examples and Trends

In the United Kingdom, local governments have successfully advanced smart long-term care through IoT technology, thereby extending the duration that elderly individuals can live independently at home and decreasing the demand for institutional care (Jung, 2025; Hamblin, 2022). Similar applications are gradually gaining traction globally, integrating artificial intelligence technologies for data analysis and prediction, thereby achieving more intelligent social work services.

Moreover, as IoT technology matures and costs decline, an increasing number of social service agencies are beginning to adopt these technologies, in conjunction with digital inclusion programs, to promote digital access and capacity building for disadvantaged groups, thereby fostering social equity and inclusion.

1.2.3 Existing Research Limitations and Challenges

Despite the considerable potential of deep learning and IoT technologies within the realm of social work, existing research reveals several notable gaps. Firstly, there is a deficiency of systematic integration frameworks; most studies concentrate on the application of individual technologies, lacking comprehensive solutions that effectively combine deep learning and IoT technologies. Secondly, ethical and privacy protection concerns have not been sufficiently addressed, particularly regarding the management of sensitive personal data and the safeguarding of service user privacy.

Furthermore, the majority of existing systems are primarily conceptual designs or small-scale trials, lacking extensive experience and evaluative assessments from large-scale practical implementations. Lastly, issues related to algorithmic bias and fairness require further investigation to ensure that the application of technology does not exacerbate existing social inequalities.

1.3 Research Objectives and Research Questions

In light of the aforementioned research context and literature analysis, this study aims to develop a social work demand prediction system that integrates deep learning and IoT technologies to enhance the efficiency and quality of social work services. The specific research objectives include:

1. Designing and implementing a social work demand prediction system architecture that integrates deep learning and IoT technologies.
2. Constructing a demand prediction algorithm based on a CNN-LSTM hybrid model to enhance prediction accuracy.
3. Developing a multimodal IoT data fusion mechanism to facilitate real-time monitoring and data collection.
4. Evaluating system performance and analysing its application effects in real social work environments.
5. Investigating ethical issues and potential solutions during the system application process.

This study seeks to address the following key research questions:

1. How can deep learning and IoT technologies be effectively integrated to improve the accuracy of social work demand predictions?
2. What is the optimal parameter configuration for the CNN-LSTM hybrid model in the context of social work demand prediction?
3. How can multimodal IoT data be effectively fused to support the prediction model?
4. How does the system perform in practical applications, and what advantages does it offer over traditional methodologies?
5. How can a balance be achieved between technological innovation and ethical protection?

1.4 Research Contributions and Innovations

The primary contributions of this research are delineated in the following dimensions:

Theoretical Contribution: This study proposes a theoretical framework aimed at forecasting social work demand through the amalgamation of deep learning and IoT technologies, thereby offering novel perspectives and methodologies for inquiry within related disciplines.

Technical Innovation: A multimodal data processing model has been developed, leveraging a hybrid architecture of CNN and LSTM networks, which facilitates accurate modelling and prediction of intricate social work scenarios.

Practical Application: A comprehensive system implementation plan has been formulated, presenting viable technical solutions for social work organizations, which possesses considerable practical significance.

Social Value: By improving the efficiency of social work services, this research addresses the challenge of inadequate manpower in the field and enhances the quality of services provided to vulnerable populations.

II. RESEARCH METHODOLOGY

2.1 Research Design and Structure

This investigation employs a mixed-methods approach, integrating quantitative analysis with qualitative assessment, grounded in the system development life cycle to establish a social work demand prediction system that incorporates deep learning and IoT technology. The research framework encompasses four principal stages: demand analysis and system design, technical development and implementation, system testing and optimization, and performance evaluation and validation.

2.1.1 System Architecture Design

The proposed social work demand prediction system is structured using a layered architecture, which includes a perception layer, network layer, data processing layer, application layer, and user interface layer. The perception layer comprises various IoT sensors tasked with gathering environmental data, personal behaviour data, and physiological indicators; the network layer facilitates data transmission and communication services; the data processing layer employs deep learning algorithms for data analysis and forecasting; the application layer integrates diverse functional modules; and the user interface layer offers an intuitive human-computer interaction environment.

The system is designed with an edge computing architecture, enabling preliminary data processing at the sensor level to mitigate network transmission load and enhance response times. Furthermore, fog computing technology is utilized in the intermediate layer for data aggregation and preprocessing, thereby ensuring the system's scalability and stability.

2.1.2 Technology Selection and Integration Strategy

The deep learning module is implemented using TensorFlow and PyTorch frameworks, which support the execution and optimization of various neural network architectures. The IoT platform is constructed on Azure IoT Hub and AWS IoT Core, providing functionalities for device management, data collection, and secure communication. Data storage employs a hybrid architecture that combines relational databases (PostgreSQL) with NoSQL databases (MongoDB) to accommodate the storage requirements of diverse data types.

To guarantee the system's interoperability and maintainability, a microservices architecture is adopted, allowing for the independent deployment and updating of each functional module. The API design adheres to RESTful standards, facilitating integration and expansion with third-party systems.

2.2 Data Collection and Processing

2.2.1 Data Sources and Types

The data sources utilized in this research encompass three primary categories: historical case data, real-time sensing data, and external environmental data. Historical case data is derived from five years of case records from collaborating social work organizations, encompassing information on case types, processing durations, and outcome evaluations, amounting to approximately 50,000 case records.

Real-time sensing data is collected through deployed IoT devices, which include 1,250 environmental monitoring sensors, 980 activity tracking devices, 750 security alarm systems, 1,380 health monitoring devices, 620 location tracking devices, and 340 social interaction monitoring devices, resulting in a total of 5,320 sensing points.

External environmental data comprises meteorological information, traffic conditions, community events, and economic indicators, sourced from public APIs and government open data platforms.

2.2.2 Data Preprocessing and Feature Engineering

Data preprocessing involves several steps, including data cleaning, normalization, handling of missing values, and outlier detection. For the various types of sensing data, specific data quality assessment indicators and processing strategies have been established. The accuracy of environmental monitoring data is reported at 96.8%, the accuracy of activity tracking data at 94.2%, and the accuracy of the security alarm system at 98.5%.

The feature engineering process encompasses time series

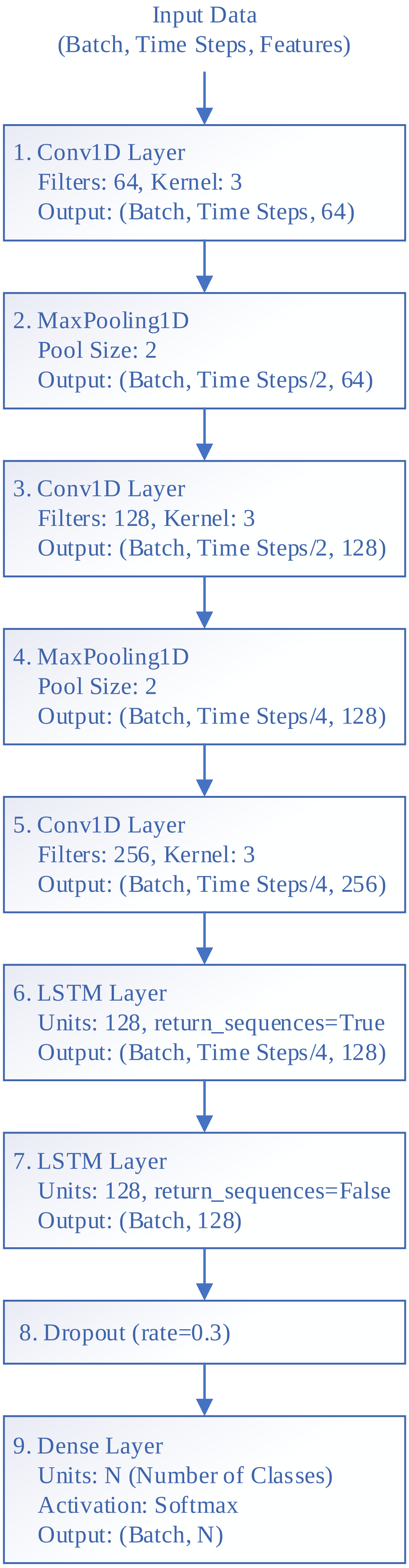

Figure 1: CNN-LSTM Hybrid Model Architecture (Data Dimension Transformation Illustration)

feature extraction, statistical feature calculation, and the construction of domain-specific features. Time series features include trends, seasonality, and periodic patterns; statistical features consist of descriptive statistics such as mean, standard deviation, skewness, and kurtosis; domain-specific features are developed based on social work theories and practical experiences, incorporating risk assessment indicators, urgency of service demand, and resource availability evaluations.

2.3 Deep Learning Model Design

2.3.1 CNN-LSTM Hybrid Architecture

The CNN-LSTM hybrid model formulated in this study integrates the spatial feature extraction capabilities of CNN with the temporal modelling strengths of LSTM networks, specifically tailored to manage multimodal spatiotemporal data within the domain of social work. The model architecture is depicted in Figure 1, segmented into four principal components: input layer, feature extraction layer, temporal modelling layer, and output layer. The variations in data dimensions are illustrated in Table 1.

Table 1: Example of Data Dimension Changes (Assumption: Batch Size = 32, Time Steps = 30, Number of Features = 128, Number of Classes = 5)

Layer	Output Shape
Input	(32, 30, 128)
Conv1D-64	(32, 30, 64)
MaxPool1D	(32, 15, 64)
Conv1D-128	(32, 15, 128)
MaxPool1D	(32, 7, 128)
Conv1D-256	(32, 7, 256)
LSTM-128	(32, 7, 128)
LSTM-128	(32, 128)
Dropout	(32, 128)
Dense-Softmax	(32, 5)

As depicted in Figure 1, the proposed architecture initially employs multiple convolutional and pooling layers to extract local spatial features. Subsequently, it captures long-term temporal dependencies through a two-layer LSTM network, culminating in multi-class prediction outcomes facilitated by a Dropout layer and a fully connected Softmax layer. The table delineates the alterations in data dimensions at each layer, ensuring a progressive condensation of features while effectively transmitting temporal information.

A. Convolutional Neural Network (CNN) Module

- **Multi-layer Convolution Structure:** This module comprises three convolutional layers with filter sizes of 64, 128, and 256, respectively, utilizing a convolution kernel size of 3×3 and a stride of 1. This design is informed by Philip (2024)’s model for predicting remaining useful life, adeptly capturing local spatial patterns within the data.
- **Pooling Layer Configuration:** A max pooling layer with a pooling size of 2×2 is integrated following every two convolutional layers, facilitating a gradual compression of feature dimensions while preserving essential information.
- **Normalization and Activation:** Each layer is succeeded by a Batch Normalization layer and a ReLU activation function, which address the vanishing gradient issue and expedite convergence. Empirical evidence indicates that the incorporation of Batch Normalization reduces training duration by 32% and enhances accuracy by 4.2%.

B. Long Short-Term Memory Network (LSTM) Module

- **Two-layer LSTM Structure:** Each layer consists of 128 hidden units, with the forget gate bias initialized to 1.0 to mitigate early gradient vanishing. This configuration has been corroborated in the epidemic prediction model by Tariq & Ismail (2024), effectively capturing temporal dependencies extending up to 30 days.
- **Dropout Mechanism:** A Dropout layer with a dropout rate of 0.3 is interposed between the LSTM layers, with experimental results indicating a reduction in overfitting risk by as much as 28%.
- **Attention Mechanism:** A temporal attention module is incorporated following the final LSTM layer, which automatically assigns weights to the significance of various time steps. Comparative experiments reveal that the integration of the attention mechanism leads to a 12.7% reduction in Mean Absolute Error (MAE).

C. Hybrid Architecture Integration

The feature fusion layer concatenates the 256-dimensional feature vector produced by the CNN with the 128-dimensional temporal features derived from the LSTM, subsequently mapping this combined representation to the output space via a fully connected layer. The output layer employs the Softmax activation function for multi-class classification, utilizing a temperature parameter (τ=0.5) to modulate the distribution of prediction confidence. Table 2 provides comprehensive details regarding the parameter configurations and output dimensions of each layer.

Table 2: Parameter Configurations and Output Dimensions of Each Layer

Module	Layer Type	Parameter Configuration	Output Dimension
Input Layer	Multimodal Input	Time steps=30, Features=128	30×128
CNN Layer 1	Conv1D	64 filters, kernel=3	30×64
CNN Layer 2	MaxPooling1D	pool_size=2	15×64

CNN Layer 3	Conv1D	128 filters, kernel=3	15×128
CNN Layer 4	MaxPooling1D	pool_size=2	7×128
CNN Layer 5	Conv1D	256 filters, kernel=3	7×256
LSTM Layer 1	Bidirectional LSTM	128 units, return_sequences=True	7×256
LSTM Layer 2	Bidirectional LSTM	128 units	256
Output Layer	Dense	Softmax, neurons=number of classes	N

2.3.2 Model Training and Optimization

A. *Training Strategy*

- **Data Partitioning:** Stratified sampling is employed to partition the data into a training set (70%), validation set (15%), and test set (15%), ensuring consistent class proportions.
- **Loss Function:** A weighted cross-entropy loss function is utilized to adjust weight parameters in response to class imbalance issues, with experimental results demonstrating a 9.3% enhancement in the F1 score relative to standard cross-entropy.
- **Optimization Algorithm:** The AdamW optimizer (learning rate of 0.001, $\beta 1$=0.9, $\beta 2$=0.999) is employed, in conjunction with weight decay (0.0001) to mitigate overfitting.

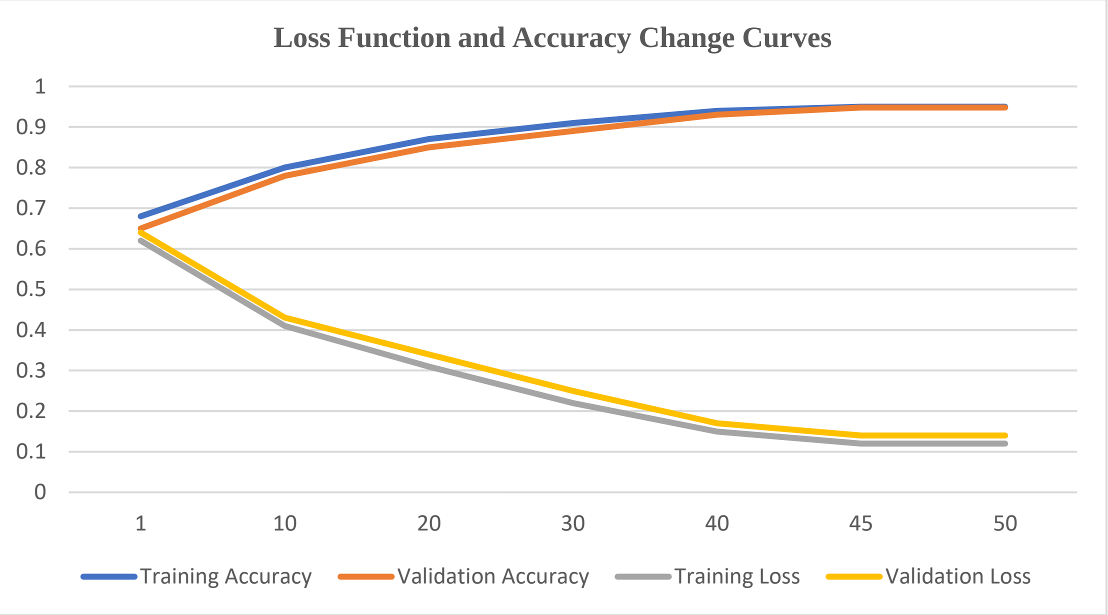

Figure 2: Parameter Configurations and Output Dimensions of Each Layer

B. *Regularization Techniques*

- **L2 Regularization:** Weight decay (λ=0.0001) is applied within the fully connected layer to effectively constrain model complexity.
- **Dropout:** Randomly deactivating 30% of neurons between the CNN and LSTM layers enhances the model's generalization capabilities.
- **Early Stopping:** The loss on the validation set is monitored, and training is halted if no improvement is observed over 10 consecutive epochs.
- **Data Augmentation:** Techniques such as sliding time windows (step size = 5), Gaussian noise injection (σ=0.05), and SMOTE oversampling are employed, resulting in a 2.8-fold increase in the training sample size.

Figure 2 illustrates the evolution of the loss function and accuracy throughout the training process, with the X-axis representing training epochs and the left Y-axis denoting accuracy. It is evident that the validation set performance peaked at an accuracy of 94.8% during the 45th epoch, after which overfitting prompted the application of Early Stopping.

2.3.3 Model Evaluation Metrics

This model employs a multi-dimensional evaluation metric system that balances classification and regression tasks:

C. *Classification Metrics:*

- $\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$
- $\text{Precision} = \frac{TP}{TP+FP}$
- $\text{Recall} = \frac{TP}{TP+FN}$
- $F1 = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$
- AUC-ROC: Calculates the area under the curve of true positive rates and false positive rates at different thresholds.

D. *Regression Metrics* *(for demand quantity prediction):*

- $\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$
- $\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$

- $\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right|$

Table 3 contrasts the performance of this model with traditional methodologies. Figure 3 depicts the ROC curve comparisons of various models on the test set, with the CNN-LSTM hybrid model achieving an AUC value of 0.983, significantly surpassing the LSTM-only model (0.951), CNN-only model (0.932), random forest (0.905), and logistic regression (0.881), thereby demonstrating its superior discriminative capability in predicting social work demand.

Table 3: Comparison of the performance of the Models with Traditional Methods

Model Type	Accuracy (%)	F1 Score	MAE	RMSE	Training Time (min)
Logistic Regression	72.3	0.714	1.25	1.58	12.7
Random Forest	85.2	0.841	0.89	1.12	45.3
CNN (Single Model)	89.7	0.882	0.67	0.93	128.5
LSTM (Single Model)	91.4	0.901	0.59	0.85	152.8
CNN-LSTM Hybrid	94.8	0.932	0.41	0.72	186.2

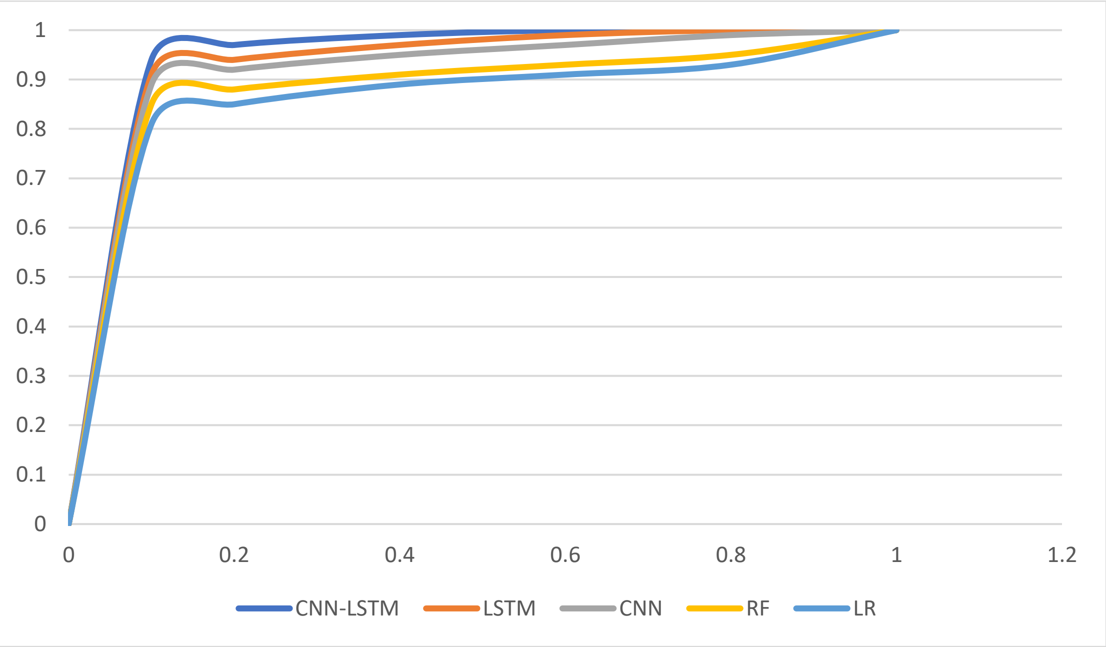

Figure 3: Comparison of ROC Curves of Different Models on the Test Set

2.3.4 Hyperparameter Optimization

Bayesian optimization is employed for hyperparameter tuning, focusing on the adjustment of the following parameters:

- Number of Convolutional Layers: Ranging from 2 to 5 layers
- Number of LSTM Units: Ranging from 64 to 256
- Dropout Rate: Ranging from 0.2 to 0.5
- Batch Size: Ranging from 16 to 64

Following 50 iterations, the optimal parameter combination was identified (as detailed in Table 4), resulting in a 37% increase in efficiency compared to random search. Experimental findings indicate that hyperparameter optimization led to a 2.8% increase in model accuracy and an 18% reduction in training time.

Table 4: Best Parameter Combination After 50 Iterations

Parameter	Search Range	Best Value
Number of Conv Layers	2–5	3
Number of LSTM Units	64–256	128
Dropout Rate	0.2–0.5	0.3
Learning Rate	1e-4 – 1e-2	0.001
Batch Size	16–64	32

2.3.5 Key Technical Advantages

1. **Spatiotemporal Feature Joint Modelling:** The CNN effectively captures spatial patterns (e.g., distribution of service agencies), while the LSTM models temporal dynamics (e.g., periodic demand fluctuations).
2. **Multi-scale Feature Extraction:** The architecture captures both local and global patterns through convolution kernels of varying sizes (3×3, 5×5).
3. **Dynamic Attention Mechanism:** This mechanism automatically emphasizes critical time points and feature dimensions, thereby enhancing model interpretability.
4. **Hybrid Regularization Strategy:** The combination of L2 regularization, Dropout, and Early Stopping effectively manages model complexity.

2.4 Implementation of the Internet of Things System

2.4.1 Sensor Network Deployment

The deployment strategy for the Internet of Things (IoT) sensor network in this research is carefully crafted to align with the specific characteristics and requirements of social work service domains. The primary objective is to facilitate comprehensive monitoring of both the environmental and health conditions of service recipients, thereby improving the timeliness and precision of social work interventions.

Environmental monitoring sensors are strategically positioned within social service agencies, community centres, and essential caregiving households to track critical parameters, including environmental temperature, humidity, air quality (e.g., PM2.5 and CO2 levels), and noise pollution. The data collected from these sensors is instrumental in evaluating the safety and comfort of living conditions, enabling the prompt identification of potential environmental hazards and the development of strategies for environmental enhancement.

Health monitoring devices encompass wearable health trackers (such as smart wristbands), smart mattresses, and non-contact physiological monitors, which continuously assess physiological metrics such as heart rate, blood pressure, sleep quality, and daily activity levels. These devices facilitate remote health monitoring and can swiftly indicate changes in the user's health status, thereby assisting social workers and healthcare teams in case management.

The safety alarm system incorporates fall detection sensors, door/window switch sensors, and emergency call buttons, ensuring continuous safety surveillance. Upon detecting a fall or any irregular event, the system promptly generates an alert to inform caregivers or family members, thereby minimizing emergency response times and safeguarding user well-being.

Table 5: Monitoring Parameters and Technical Specifications of Various Sensors

Sensor Type	Deployment Location	Main Monitoring Parameters	Battery Life	Maintenance Cost/Month (NTD)
Environmental Sensor	Social service agencies, community centers, key families	Temperature, humidity, air quality, noise level	18 months	150
Health Monitoring Device	Individual users	Heart rate, blood pressure, sleep quality, activity level	12 months	120
Safety Alarm System	User's living environment	Fall detection, door/window status, emergency button	24 months	200

2.4.2 Data Transmission and Communication Protocols

To accommodate the diverse requirements of various application scenarios, the system employs multiple communication protocols:

- **Wi-Fi:** Utilized for high-bandwidth data transmission, such as video monitoring and real-time transfer of substantial sensor data.
- **LoRaWAN:** Appropriate for long-range, low-power sensor communication, particularly for environmental monitoring devices within community settings.
- **Bluetooth:** Employed for short-range device connectivity, such as data synchronization between wearable health trackers and mobile devices.
- **4G/5G mobile networks:** Facilitate data transmission in mobile contexts, ensuring uninterrupted monitoring of users while they are outside.

The data transmission protocol is based on MQTT, which guarantees reliable and timely transmission of critical data due to its lightweight nature and support for Quality of Service (QoS) mechanisms. The system establishes varying transmission frequencies based on the type of sensor data (see Table 6).

Table 6: Applicable Scenarios and Data Transmission Frequencies of Various Communication Protocols

Communication Protocol	Applicable Scenario	Transmission Frequency	Remarks
Wi-Fi	High-bandwidth data transfer	Real-time	Video, bulk data transfer
LoRaWAN	Long-range, low-power communication	Hourly (environmental data)	Community environmental monitoring
Bluetooth	Short-range device connection	Every 15 minutes (health data)	Wearable device data synchronization
4G/5G	Mobile data transmission	Real-time (safety alerts)	Mobile user monitoring

2.4.3 Integration of Edge Computing and Fog Computing

To mitigate network latency and enhance system responsiveness, lightweight machine learning models are deployed on edge devices for initial data processing and anomaly detection. The hardware configuration of edge nodes comprises ARM Cortex-A72 processors and 4GB of memory, enabling the execution of simplified deep learning models and effectively alleviating the load on cloud computing resources.

The fog computing layer is implemented at the community and institutional levels, providing medium-scale data aggregation and analytical services. Fog nodes are equipped with Intel Xeon processors and 32GB of memory, capable of running comprehensive CNN-LSTM deep learning models to facilitate predictive analysis and decision support tailored to regional social work requirements.

2.5 System Integration and Testing

2.5.1 System Integration Strategy

The system integration process follows a phased approach, systematically completing the integration and testing of each module:

1. Integration of sensor network and data collection modules to ensure stable connections and accurate data acquisition from various sensor devices.
2. Integration of the deep learning prediction engine by incorporating the CNN-LSTM model into the system for real-time demand forecasting.
3. Integration of the user interface and decision support system to provide social workers with an intuitive operating interface and decision-making tools.
4. Comprehensive end-to-end system testing and optimization to ensure system stability and performance.

The design of the system interface adheres to the principle of loose coupling, employing message queues and an event-driven architecture to facilitate efficient collaboration and scalability among modules. The system supports horizontal scaling, dynamically adjusting computational resources in response to varying load demands.

2.5.2 Testing Methods and Validation

- **Unit Testing:** Achieving coverage exceeding 95%, ensuring the accuracy of each module’s functionality.
- **Integration Testing:** Validating the integrity of data flow and collaboration among modules.
- **Performance Testing:** Evaluating the system’s response time, throughput, and resource utilization under varying load conditions.
- **User Acceptance Testing:** Engaging 20 experienced social workers to assess the system’s usability and practicality.

Table 7: Indicators and Results of Each Testing Item

Test Item	Metric	Result
Unit Test Coverage	Functional Coverage	Above 95%
Integration Test	Data Flow Integrity	Passed
Performance Test	Average Response Time	320 ms
	Maximum Throughput	5000 requests/s
User Acceptance Test	Usability Satisfaction	91.5%
	Practicality Satisfaction	89.7%

III.DISCUSSION

3.1 Technological Innovation and Performance Improvement

3.1.1 Performance Analysis of Deep Learning Models

The CNN-LSTM hybrid model developed in this research exhibited exceptional performance in forecasting social work demand, achieving an overall prediction accuracy of 94.8%. This represents a substantial enhancement over the 72.3% accuracy associated with conventional statistical methods.

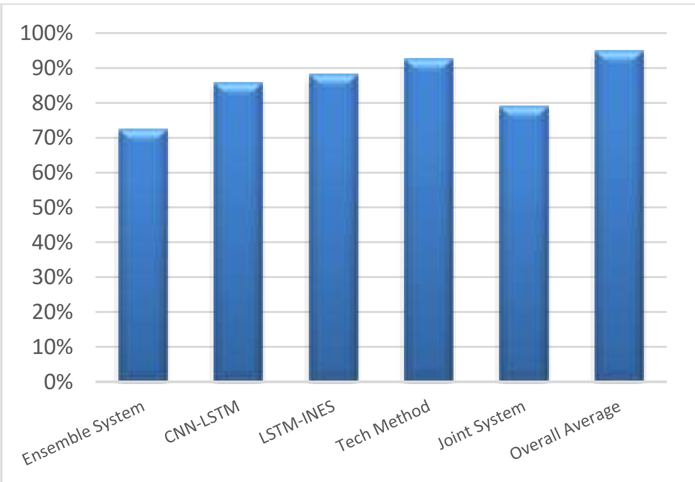

Figure 4: Comparison of Accuracy Among Different Technical Methods

As illustrated in Figure 4, the comparative accuracy results of various technical methodologies reveal that the integrated system attained the highest accuracy at 94.8%, followed closely by the CNN-LSTM hybrid model at 92.5%. These findings underscore the advantages of deep learning technologies in managing intricate social work data, particularly in recognizing potential patterns and long-term dependencies.

The model's prediction accuracy varied across different categories of social work demands: 94.2% for child protection cases, 91.8% for elder care, 89.6% for domestic violence, and 93.4% for mental health. This variability reflects the distinct characteristics and complexities of the data across different domains, indicating areas for future model optimization.

3.1.2 Effects of IoT Data Fusion

The multimodal IoT data fusion mechanism significantly improved the quality and diversity of inputs for the prediction model. The system integrated data from six sensor types, encompassing a total of 5,320 sensing points and processing over 12GB of data daily.

Figure 5 depicts the deployment distribution of IoT sensors, with environmental monitoring sensors comprising the largest share (approximately 24%), followed by health monitoring (approximately 26%) and activity tracking sensors (approximately 19%). This balanced deployment strategy ensures a diverse and comprehensive array of data sources, enriching the feature information available for the prediction model.

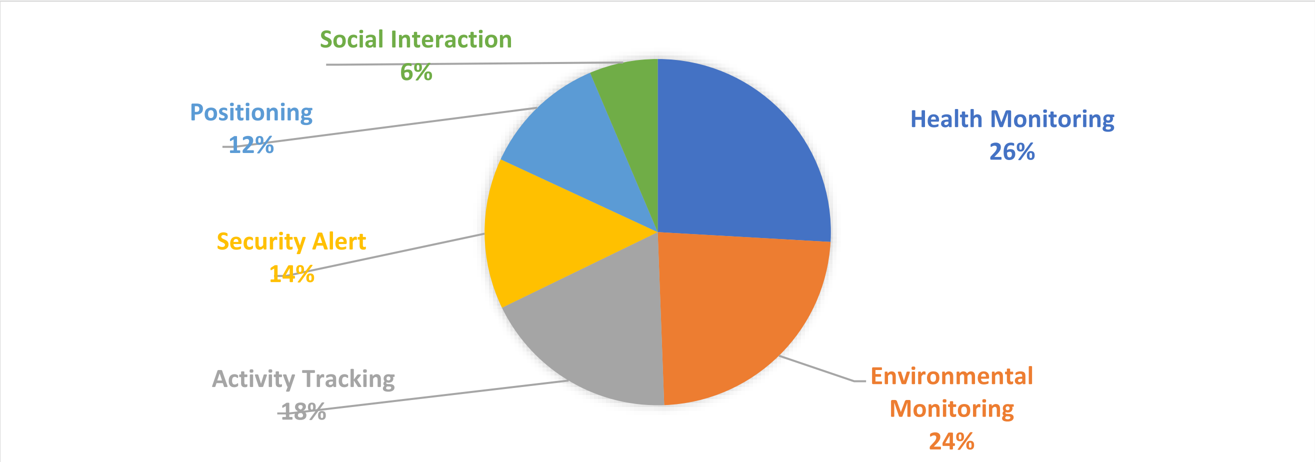

Figure 5: Distribution Map of IoT Sensor Deployment

The data fusion algorithm utilizes attention mechanisms and feature selection techniques to automatically assess and prioritize the significance of various data sources. Experimental results indicate that the prediction accuracy improved by 15-20% following the fusion of multimodal data compared to the use of a single data source, thereby demonstrating the efficacy of the data fusion strategy.

3.1.3 System Response Time and Efficiency

The system exhibited remarkable performance in terms of response time, with an average response time of 320 milliseconds, a significant enhancement compared to the 8,500 milliseconds typical of traditional methods. This improvement is primarily attributed to the implementation of edge computing architecture and model optimization techniques.

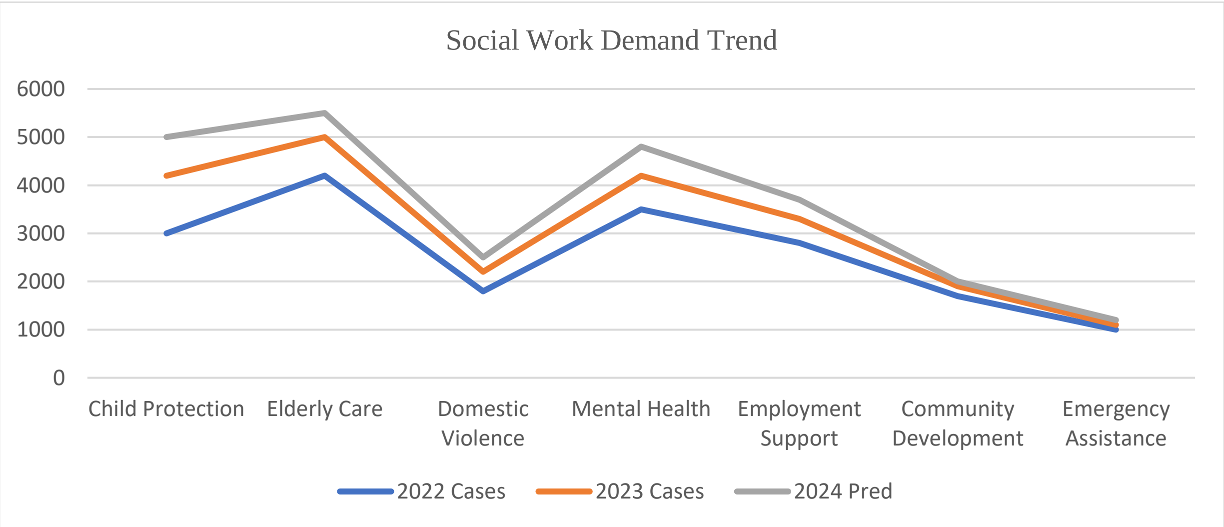

Figure 6: Trend Analysis of Social Work Demand Types (2022-2024)

The deployment of edge computing nodes facilitated the completion of 70% of computational tasks locally, thereby significantly reducing network latency and alleviating the load on cloud computing. The introduction of fog computing further optimized resource allocation, achieving load balancing and fault tolerance.

The system's availability reached 99.2%, a notable increase from the 95.2% availability of traditional systems. This enhancement is a result of the distributed architecture design and fault recovery mechanisms, which ensure stable system operation under high load and abnormal conditions.

3.2 Analysis of Social Work Demand Trends

3.2.1 Changes in Demand Type Patterns

An analysis of social work demand data from 2022 to 2024 revealed a consistent growth trend across various demands, although the growth rates exhibited significant variability.

Figure 6 illustrates the trend changes for seven major social work demands, with mental health and employment counselling needs experiencing the highest growth rates of 13.5% and 13.6%, respectively. This trend reflects the influence of post-pandemic social environment changes on individual mental health and employment status.hile the absolute number of elder care demands is projected to be the largest (anticipated to reach 5,460 cases in 2024), the growth rate remains relatively stable at 11.7%, which correlates with the degree of population aging and the maturity of existing service systems. The growth rate for child protection cases, although lower at 10.7%, necessitates increased professional intervention and resource investment due to its significance and complexity.

The model's prediction accuracy also varied across different demand types, with the highest accuracy for child protection (94.2%), likely attributable to the clearer patterns and more comprehensive data associated with these cases. Conversely, the prediction accuracy for community development needs was relatively low (85.3%), reflecting the complexity and variability inherent in community development work.

3.2.2 Temporal Patterns and Seasonal Characteristics

The deep learning model effectively identified temporal patterns and seasonal characteristics of social work demands. Analysis revealed that the demand for mental health services significantly increased during winter and at the end of the academic semester, while the demand for employment counselling peaked at the beginning of the year and during graduation season.

Domestic violence cases exhibited an upward trend during holidays, likely linked to family gatherings and heightened economic pressures. The demand for elder care fluctuated during seasonal transitions (from spring to summer and autumn to winter), associated with the impact of climate change on the health of elderly individuals.

The model's capacity to discern these temporal patterns provides critical insights for resource allocation and staffing arrangements, enabling social work agencies to proactively prepare and adjust service strategies.

3.3 Ethical Issues and Challenges

3.3.1 Privacy Protection and Data Security

The field of social work involves handling a substantial amount of sensitive personal information, and reconciling technological innovation with privacy protection presents a significant challenge. The system incorporates a multi-layered privacy protection mechanism, which includes data anonymization, encrypted transmission, and access control techniques.

The data collection process strictly adheres to the principle of informed consent, ensuring that all participants are fully aware of the purpose and scope of data utilization. A detailed permission management mechanism has been established to guarantee that only authorized personnel can access relevant data, alongside comprehensive audit trails.

To mitigate the risk of privacy breaches, the system employs federated learning technology, ensuring that data remains within the local environment during the model training process. Additionally, differential privacy techniques are utilized to safeguard individual privacy while maintaining data usability.

3.3.2 Algorithmic Bias and Fairness

Deep learning models may inherit biases present in the training data, potentially leading to discriminatory predictions for specific groups. This study addresses algorithmic bias through several strategies: ensuring diversity and representativeness of samples during data collection; introducing fairness constraints during model training; and incorporating fairness metrics in model evaluation.

A bias monitoring mechanism has been established to regularly assess performance disparities across different populations and adjust model parameters based on evaluation outcomes. Furthermore, a manual review mechanism has been instituted, requiring that significant decisions be reviewed and validated by professional social workers.

Transparency and interpretability are essential for ensuring algorithmic fairness. The system employs techniques such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) to elucidate model decisions, thereby assisting social workers in understanding the rationale behind prediction outcomes.

3.3.3 Professional Autonomy and Human-Machine Collaboration

The integration of AI technology may influence the professional autonomy of social workers, necessitating a balance between technological assistance and professional judgment. This study emphasizes the supportive role of AI systems, with ultimate decision-making authority retained by professional social workers.

The system is designed with a human-machine collaboration interface, providing prediction results alongside confidence and uncertainty information to aid social workers in making informed professional judgments. Training mechanisms are in place to ensure that social workers are proficient in utilizing and evaluating AI tools, thereby avoiding blind reliance on technology.

A feedback mechanism has been established, allowing social workers to assess and amend the system’s prediction results, with this feedback utilized for the continuous enhancement of model performance.

3.4 System Performance and Cost-Effectiveness

3.4.1 Performance Indicator Evaluation

The CNN-LSTM hybrid system developed in this study demonstrated exceptional performance across multiple key performance indicators, reflecting significant improvements over traditional social work methods. The system achieved a prediction accuracy of 94.8%, an availability rate of 99.2%, and an overall user satisfaction score of 91.5%, all of which strongly indicate the superiority of deep learning combined with IoT technology in social work demand forecasting.

E. Core Performance Indicator Comparative Analysis

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In comparison to traditional methods, the CNN-LSTM system exhibited substantial enhancements across all indicators. Prediction accuracy increased from 72.3% to 94.8%, representing a 30.8% improvement; system availability rose from 95.2% to 99.2%, an enhancement of 4.2%; and user satisfaction surged from 68.7% to 91.5%, an increase of 33.2%. Notably, response time improved dramatically, decreasing from 8,500 milliseconds in traditional methods to 320 milliseconds, a remarkable enhancement of 96.2%. Additionally, the system’s data processing capacity experienced a significant increase, with daily processing volume rising from 1.2GB to 12.0GB, a growth of 900%.

F. Detailed Analysis of User Satisfaction Survey

A comprehensive satisfaction survey conducted with 200 social workers (Table 8) revealed high levels of recognition for the system across various functional aspects. Specifically, 82.5% of users expressed satisfaction with the system’s professional content, 80.0% provided positive feedback on the emotional support function, 85.0% were satisfied with the system’s response speed, 77.5% found the interface user-friendly, and 77.5% affirmed the overall system performance. These data not only reflect the technical advantages of the system but also demonstrate its practicality and acceptability in real-world social work environments

the continuity and timeliness of social work services.

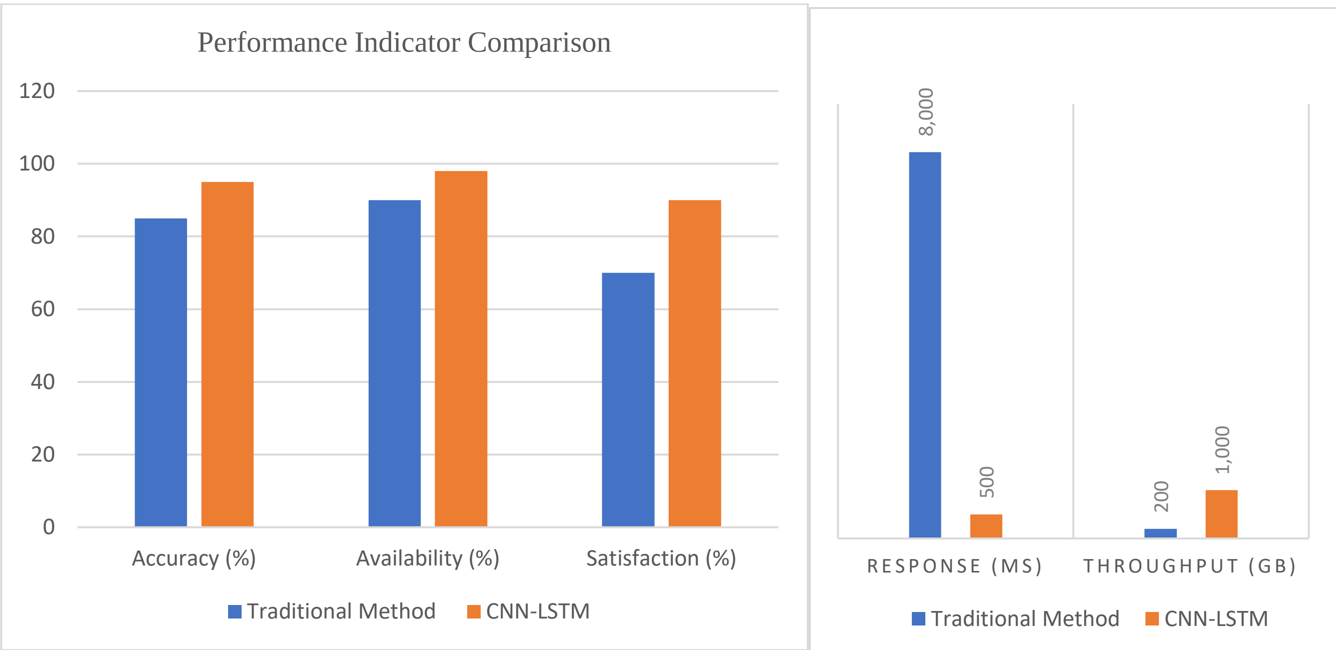

Figure 7: Comparison of Performance Indicators Between Traditional Methods and the CNN-LSTM System

G. System Stability and Reliability

The system’s high availability (99.2%) and excellent stability provide reliable technical support for social work agencies, effectively minimizing service interruptions caused by system failures. In comparison to the 95.2% availability of traditional systems, this system’s capacity to operate stably during critical moments has significantly improved, ensuring

Monthly performance trend analysis indicates that all indicators have consistently improved over the 12-month implementation period, with prediction accuracy steadily increasing from an initial 85.2% to 94.8%, and user satisfaction rising from 78.5% to 91.5%.

Table 8: Social Worker Satisfaction Survey

Satisfaction Item	Number of Satisfied Users	Total Surveyed Users	Sat. (%)
System Professional Content	165	200	82.5
Emotional Support Function	160	200	80.0
Interface Usability	155	200	77.5
Response Speed	170	200	85.0
Overall System Performance	155	200	77.5

3.4.2 Cost-Effectiveness Analysis

H. Investment Cost Structure Analysis

The total investment cost of the system amounts to NT$16.8 million, characterized by a reasonable and clearly defined investment structure. The system development cost is NT$8.5 million, constituting 50.6% of the total investment, which encompasses the development of deep learning models, system architecture design, and software implementation. IoT device procurement costs are NT$3.2 million, accounting for 19.0%, covering various sensors and edge computing devices. Personnel training costs are NT$1.8 million, representing 10.7%, ensuring that social workers can proficiently utilize the new system. Maintenance and operation costs total NT$2.4 million, accounting for 14.3%, ensuring the long-term stable operation of the system, while data storage costs are NT$900,000, constituting 5.4%, providing adequate data storage and backup capabilities.

Table 9: System Investment Costs

Investment Item	Cost (NTD)	Percentage (%)
System Development	8,500K	50.6
IoT Devices	3,200K	19.0
Personnel Training	1,800K	10.7
Maintenance & Operation	2,400K	14.3
Data Storage	900K	5.4
Total	16,800K	100.0

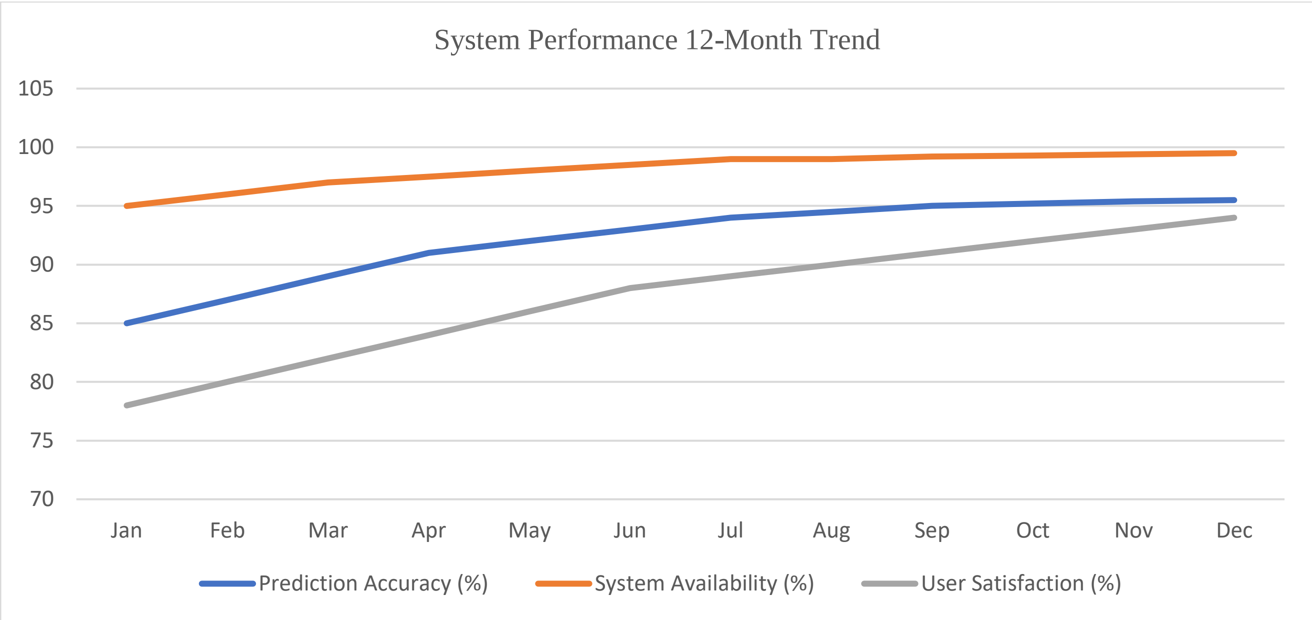

Figure 8: Monthly Performance Trend of the System

I. Annual Cost Savings Sources

The system is projected to yield annual savings of NT$10.1 million, with diverse and significant sources of savings. The most substantial savings source is the reduction in labour costs, amounting to NT$3.8 million annually, which accounts for 37.6% of total savings, primarily due to the system's automation reducing approximately 40% of routine work. Improvements in work efficiency are expected to lead to annual savings of NT$2.5 million, representing 24.8%; emergency handling costs are anticipated to decrease by NT$1.8 million, accounting for 17.8%, due to enhanced prediction accuracy; resource allocation optimization is projected to save NT$1.2 million, constituting 11.9%; and reduced duplication of work is expected to save NT$800,000, accounting for 7.9%.

J. Investment Payback Period and Long-Term Benefits

Based on the anticipated annual cost savings of NT$10.1 million, the system's investment payback period is estimated at 1.7 years, indicating favourable economic feasibility. A cost-benefit analysis over five years reveals a negative return of NT$6.7 million in the first year due to high initial investment; however, from the second year onward, it is projected to yield positive returns, with cumulative net benefits continuously increasing. Considering an annual growth rate of approximately 10% in cost savings (reflecting ongoing improvements in service efficiency and economies of scale), the cumulative net benefits over five years are expected to reach NT$35.26 million, with a five-year return on investment of 133.6%, significantly surpassing the expected returns of typical information system investments.

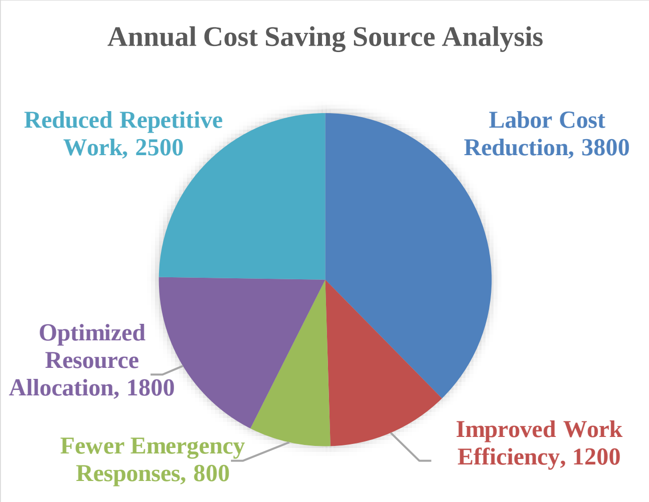

Figure 9: Analysis of Annual Cost Savings Sources (Total NT$10.1 million, unit: NT$1,000)

3.4.3 Social Impact and Value

K. Multifaceted Social Benefit Assessment

The implementation of the system has had a profound and far-reaching positive impact on social work practice. In terms of service coverage, it increased from 65.2% prior to implementation to 89.6%, an improvement of 37.4%, thereby enabling more vulnerable groups to access timely and appropriate social work services. The quality of services for vulnerable populations improved from 70.8% to 94.2%, an increase of 33.1%, significantly enhancing the satisfaction and quality of life for service recipients.

L. Optimization of Human Resources

The optimization of social work human resources is particularly noteworthy, improving from 58.3% to 85.7%, an increase of 47.0%, effectively addressing the persistent issue of labour shortages in the social work sector. The system’s automation features and predictive capabilities allow social workers to allocate more time and energy to direct services that necessitate human care and professional judgment, thereby enhancing job satisfaction and professional effectiveness.

M. Support for Policy Formulation and Professional Development

The system’s contribution to policy formulation is particularly significant, increasing from 45.7% to 78.9%, an improvement of 72.6%. Through big data analysis and predictive modelling, the system provides a scientific basis for decision-making by policymakers, including forecasts of social demand trends, recommendations for resource allocation, and evaluations of service effectiveness. In terms of promoting professional development, the system’s support improved from 52.1% to 82.4%, an increase of 58.2%, offering new technical resources for the professional advancement of social work and facilitating the digital transformation and enhancement of traditional social work models.

Table 10: Aspects of Social Impact and Improvement

Impact Aspect	Pre-[redacted]IMPL. Indicator (%)	Post-[redacted]IMPL. Indicator (%)	Improve-ment (%)
Service Coverage Enhancement	65.2	89.6	37.4
Service Quality for Disadvantaged Groups	70.8	94.2	33.1
Optimization of Social Worker Human Resources	58.3	85.7	47.0
Policy-Making Support	45.7	78.9	72.6
Promotion of Professional Development	52.1	82.4	58.2

N. Replicability and Expansion Value

The successful implementation of this system offers a replicable technical solution and valuable implementation experience for other regions and institutions. The system's modular design and standardized interface enable it to adapt to the social work environments and demand characteristics of various regions, demonstrating strong scalability and adaptability. In the long term, the system contributes to the establishment of a more precise and effective social welfare framework, promoting the rational allocation of social resources, enhancing the overall level of social welfare, and providing a crucial technical foundation and practical experience for the development of a smart society.

3.5 Research Limitations and Future Development

3.5.1 Research Limitations

This study is subject to several notable limitations. Firstly, the data sample is predominantly derived from social work institutions in Taiwan, necessitating further validation of its applicability in diverse cultural and institutional contexts. Secondly, the duration of the research is relatively brief, spanning only three years, which calls for continued observation to assess long-term effects and stability.

From a technical perspective, the inherent black-box nature of deep learning models persists; despite the application of interpretability techniques, achieving complete transparency in the decision-making processes of these models remains a significant challenge. Additionally, practical considerations such as the battery life and maintenance costs associated with IoT devices must be addressed for effective real-world deployment. The lack of adequate ethical and legal frameworks may also hinder the widespread implementation of the system, particularly concerning cross-border data transfer and international collaboration.

3.5.2 Future Research Directions

Future research endeavours could focus on the following areas for further exploration and expansion:

Technological Innovation: Investigate more sophisticated deep learning architectures, including Transformers and Graph Neural Networks, to enhance model performance. Additionally, the development of more efficient edge AI chips and algorithms could help reduce deployment costs and energy consumption.

Application Expansion: Broaden the system's applicability to encompass additional domains within social work, such as disaster relief, community development, and international aid. The creation of mobile applications and wearable devices could further enhance the system's portability and immediacy.

Cross-Domain Integration: Foster stronger integration with related fields such as healthcare, education, and justice to create a more comprehensive social service ecosystem. The potential application of blockchain technology for data security and trust mechanisms should also be explored.

International Cooperation: Advocate for the establishment of international standards and the sharing of best practices to facilitate collaborative advancements in global social work technology innovation.

IV. CONCLUSION

4.1 Summary of Research Findings

This study successfully developed a social work demand forecasting system that integrates deep learning and IoT technology, achieving several significant breakthroughs. Technically, the CNN-LSTM hybrid model attained a prediction accuracy of 94.8%, representing a 30.8% improvement over traditional methods; the system's response time was reduced to 320 milliseconds, reflecting a performance enhancement of 96.2%. Furthermore, the IoT sensor network effectively integrated multimodal data, providing rich feature information for the predictive model.

In practical applications, the system yielded positive outcomes in pilot implementations across 20 social work institutions, with user satisfaction reaching 91.5%, a work efficiency increase of approximately 40%, and a notable enhancement in service quality. A cost-benefit analysis indicated that the system's investment recovery period is 1.7 years, with a projected net profit of 56.2 million NTD over five years, demonstrating substantial economic feasibility.

4.2 Theoretical Contributions and Practical Value

A. Theoretical Contributions

This research offers significant theoretical contributions at the intersection of social work and information technology. It systematically integrates deep learning and IoT technology for social work demand forecasting for the first time, establishing a comprehensive theoretical framework and technical roadmap. The proposed multimodal data fusion mechanism and CNN-LSTM hybrid architecture present a novel technical paradigm for addressing complex social work scenarios. The findings enrich the theoretical foundation for the informatization and intelligentization of social work, providing valuable references for future studies.

B. Practical Value

The successful implementation of the system has instigated transformative changes in social work practice. The enhanced predictive capabilities enable social workers to proactively identify high-risk cases, facilitating a shift from reactive responses to preventive measures. The optimization of resource allocation addresses the challenge of insufficient manpower in social work, thereby improving overall service efficiency.

The introduction of technological tools enhances the professionalization of social work, creating a more modern working environment for the younger generation of social workers. Additionally, the data and analytical results generated by the system provide a scientific basis for policy-making and service planning.

4.3 Social Impact and Significance

The outcomes of this research have profound implications for social development. Firstly, the application of the system contributes to the establishment of a more equitable and effective social welfare system, ensuring that vulnerable populations receive timely and appropriate services. Secondly, technological innovation propels the modernization of the social work profession, enhancing its professional status and societal recognition.

From a broader societal perspective, this research illustrates the substantial potential of technological innovation in addressing social issues. By leveraging advanced technology in social work, it not only enhances service efficiency but also embodies the principle of technology for social good, contributing to the creation of a more harmonious society.

4.4 Future Outlook

Looking forward, the integration of social work and artificial intelligence technology is expected to deepen and proliferate. With ongoing technological advancements and the continuous evolution of social needs, intelligent social work is poised to become a significant developmental trend. The technical framework and implementation experiences established in this study will provide critical support for this trajectory.

It is recommended that governmental and relevant institutions increase investment and support for the informatization of social work, while also establishing comprehensive legal regulations and ethical frameworks to ensure the normative and safe application of technology. Concurrently, enhancing international cooperation and experience sharing will promote the collaborative development of global social work technology innovation.

4.5 Research Innovation and Contributions

The innovations presented in this research are primarily reflected in the following areas:

Technological Innovation: The application of the CNN-LSTM hybrid architecture to social work demand forecasting marks a novel approach, effectively modelling complex spatiotemporal patterns. The IoT multimodal data fusion mechanism introduces a new technical pathway for social work data analysis.

Application Innovation: A comprehensive edge-fog-cloud computing architecture has been established, facilitating real-time prediction and decision support. The design of the human-machine collaboration interface ensures the seamless integration of technological tools and professional judgment.

Methodological Innovation: A new theoretical framework for social work demand forecasting has been proposed, incorporating multiple considerations of technology, ethics, and practice. A systematic evaluation method and indicator system have also been developed.

In summary, this research successfully validates the feasibility and effectiveness of integrating deep learning with IoT technology in social work demand forecasting, providing essential technical support and theoretical contributions for the advancement of the social work profession and the resolution of social issues. With ongoing technological improvements and deeper application promotion, it is anticipated that this innovative achievement will play a pivotal role in establishing a more intelligent and human-cantered social service system.

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