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University of Diyala
College of Science
Computer Science Department

Deep learning model for detecting sick building syndrome

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By

Haider Qasim Flayyh

Supervised by

Professor Dr. Jumana Waleed Salih

Professor Dr. Amer Mohammed Ibrahim

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ABSTRACT

The integration of information technology into civil engineering represents a significant advancement in the intelligent monitoring and control of built environments, thereby enhancing safety, efficiency, and user comfort. A crucial aspect of this integration is indoor air quality (IAQ), which has a significant impact on human health. Poor IAQ, particularly in hospitals, can lead to sick building syndrome (SBS), resulting in symptoms such as headaches, fatigue, and cognitive impairment.

This dissertation propose a deep learning (DL) framework for SBS, combining indoor air quality classification with environmental condition prediction. The system was designed to work with real data from environmental sensors collected over a year at Baqubah Teaching Hospital, comprising over 523,524 samples with ten key features. The hybrid 1D-CNN-BiLSTM model achieved the highest classification accuracy of 94.8%. The model was further optimized using a multi-stage framework. While these improvements reduced accuracy to 92%, they significantly improved computational efficiency; inference time decreased from 20.8 seconds to 0.66 seconds, and file size decreased from 5.17 MB to 1.72 MB.

In addition to classification, the model was also used to predict thermal comfort indicators, specifically temperature and relative humidity. Utilizing a sliding window of 120 time steps, the model effectively predicted environmental conditions for the next 60 minutes, achieving R^2 exceeding 0.99 for both variables. This confirms its robustness and reliability in environmental predictions.

Chapter One

General Introduction

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1.1 Introduction

Human efforts have continuously aimed to improve living standards, evolving from basic shelters to technologically advanced buildings that provide safety, comfort, and energy efficiency. However, these advancements introduce new challenges related to maintaining IAQ. As modern societies spend a significant portion of their time indoors, whether at home, in offices, or in healthcare facilities, the IAQ has become a critical factor for health and well-being. Poor IAQ has been linked to a wide range of adverse health outcomes, including respiratory problems, cognitive impairments, general discomfort, and reduced productivity [1].

The issue of IAQ is particularly critical in healthcare settings, such as hospitals, where vulnerable patients and healthcare workers are exposed to complex indoor environments. High occupancy rates, frequent human activity, and the presence of sensitive individuals increase the risk of exposure to airborne pollutants and infectious agents [2]. According to the World Health Organization (WHO), poor IAQ contributes to nearly 3.2 million deaths each year, underlining the global need for effective monitoring, management, and mitigation strategies to protect public health [3].

SBS is a major concern associated with poor IAQ, causing symptoms such as headaches, fatigue, eye irritation, and respiratory issues, which often subside when individuals leave the affected environment. These symptoms are linked to low ventilation, temperature and humidity fluctuations, and high concentrations of pollutants including Carbon Dioxide (CO_2), Total

Volatile Organic Compounds (TVOCs), particulate matter (PM2.5, PM10), and Ozone (O_3). Managing SBS is crucial in hospitals to protect patients with chronic health conditions [4].

Artificial Intelligence (AI), particularly DL, has proven effective for IAQ assessment. DL models can capture complex, nonlinear relationships among environmental variables, providing robust classification and prediction capabilities while addressing imbalanced data issues. This enables early detection of patterns that may precede SBS symptoms[5][6][7].

Forecasting IAQ and associated thermal comfort parameters, such as temperature and relative humidity, is critical for preventing SBS and ensuring a healthy indoor environment [8]. Accurate predictions enable building managers and healthcare staff to implement timely control measures, optimize ventilation, and maintain comfortable and safe conditions for occupants. By combining IAQ classification with predictive modeling, AI-driven systems provide actionable insights that support proactive management, reduce health risks, and improve overall building performance [9][10].

1.2 Related Work

In this section, DL approaches for predicting SBS were reviewed, with special attention paid to monitoring IAQ, temperature, and relative humidity. Poor IAQ in environments such as hospitals, commercial environments, and households is usually associated with SBS. Therefore, its prediction can benefit from the application of advanced DL techniques. Furthermore, an overview of several DL models used in previous studies, highlighting their strengths, limitations, and data sources, is provided in Table (1.1).

- ***Shi et al. [11], (2018),*** proposed an improved Backpropagation (BP) neural network to predict indoor temperature and humidity in industrial environments. The model was trained and validated on real environmental data from Chongqing, China, and achieved high accuracy, with determination coefficients of 0.9897 for temperature and 0.9778 for humidity. These results confirmed the effectiveness of the proposed method in enhancing prediction performance and demonstrated its potential for maintaining proper environmental conditions in industrial applications.
- ***Xu et al. [12], (2018),*** proposed an advanced LSTM model combined with an error correction mechanism to enhance indoor temperature prediction in public buildings. By applying co-integrated data, the modified model addressed the limitations of conventional approaches and improved both prediction accuracy and directional reliability. Validation showed an increase in R^2 values ranging from 1% to 9.73% for forecasts five minutes ahead, confirming the model's effectiveness for building environment management and its potential to reduce SBS-related issues.
- ***Zhao et al. [13], (2018),*** focused on using DL for forecasting air quality classification across three industrial cities in the United States. An RNN was applied for air quality forecasting instead of the SVM and RF models,

to improve the predictive quality of the time-series air quality data. The RNN, which handles sequential data with its memory mechanism, improved the prediction performance of the non-memory model by a large margin. The results stress the relevance of the DL for air quality prediction and how this can also enhance public wellness by helping with the mitigation of air pollution.

- ***Jin et al. [14], (2019),*** proposed a DL- based approach for predicting the optimum indoor air temperature to achieve thermal comfort in smart homes. The study examined the relationship between indoor air temperature and occupant comfort using the PMV model and developed two DNN architectures: one for regression-based prediction and another for classification-based modeling. Validation results showed high accuracy, with an average absolute error of about 0.1°C, which was sufficient to support automatic air-conditioning control without requiring direct user intervention.
- ***Parashar and Sonker [15], (2019),*** focused on the application of DNNs for air quality classification, emphasizing the role of hyperparameter optimization through Talos to improve model performance. By applying the optimized DNN framework to air quality data, the study achieved enhanced accuracy and efficiency compared to conventional trial-and-error model selection. The results confirmed that properly tuned DL models can provide effective solutions for monitoring and predicting air pollution in response to the global decline in air quality.
- ***Elmaz et al. [16], (2021),*** proposed the CNN-LSTM model to improve indoor temperature prediction in HVAC systems. In this approach, the convolutional layers were employed for feature extraction, while the LSTM component captured temporal dependencies for sequential learning. The model was evaluated against MLP and standalone LSTM

architectures under a closed-loop prediction scheme across horizons of 1, 30, 60, and 120 minutes. Results demonstrated that CNN-LSTM consistently outperformed the other models, achieving superior accuracy and effectively reducing error accumulation, with R^2 values exceeding 0.9 for 120-minute forecasts.

- ***Eka et al. [17], (2022),*** focused on sequence-to-sequence deep learning models (LSTM seq2seq and GRU seq2seq) for predicting temperature and relative humidity in enclosed buildings such as the Solar Dryer Dome. Compared with standard LSTM and GRU models, the seq2seq variants achieved lower MAE, with the GRU improving by 0.03013 and the LSTM by 0.00941. The results validated the effectiveness of seq2seq architectures for environmental prediction, with scope for further enhancement through optimization.
- ***Hou et al. [18], (2022),*** proposed a hybrid CNN-LSTM model for hour-by-hour air temperature prediction. In this approach, CNN was used to reduce data dimensionality, while LSTM captured long-term temporal dependencies. The model was trained on more than 60,000 meteorological data points collected over 20 years in Yinchuan, China. Results showed that CNN-LSTM outperformed standalone CNN and LSTM models, achieving an accuracy of 1.02 and an MSE of 0.7258. These findings demonstrated the robustness and effectiveness of the hybrid approach in modeling nonlinear relationships and long time-series data for temperature prediction.
- ***Ozbek et al. [19], (2022),*** focused on LSTM and ANFIS models enhanced with fuzzy c-means (FCM) for forecasting next-day relative humidity (RH) across different climatic regions in Turkey. The models were trained and tested on meteorological data, with performance evaluated using RMSE, MAE, and R^2 metrics. In Erzurum province, the LSTM

achieved an MAE of 5.76%, RMSE of 7.51%, and R^2 of 0.892, while ANFIS achieved an MAE of 5.95%, RMSE of 7.67%, and R^2 of 0.887. The results confirmed the efficiency of both approaches for RH prediction, highlighting their value for climatological and environmental applications.

- ***Bao et al. [20], (2022),*** suggested the hybrid FL-CNN-LSTM model that integrates fuzzy logic with a CNN-LSTM neural network for indoor air quality (IAQ) prediction. The model was applied to an indoor PM2.5 sensor dataset collected in Shanghai between November 2016 and March 2017, and implemented using the PyTorch framework. Comparative analysis against LSTM and CNN-LSTM baselines showed that the proposed FL-CNN-LSTM achieved superior accuracy and produced more interpretable results. These findings highlighted its potential for improving IAQ monitoring and enabling smart IoT-based control strategies to promote.
- ***Di Già and Papurello [21], (2022),*** proposed a hybrid model for LSTMs indoor temperature forecasting at the Energy Center, Turin. Using HVAC data and outdoor temperature, it predicts 2, 5, and 24 hours with high accuracy, achieving an average RMSE of 0.1°C across different floors and horizons. The study highlights its potential for predictive control, energy demand management, and reducing carbon emissions in buildings.
- ***Marzouk et al. [22], (2022),*** developed an IoT-based monitoring system integrated with deep learning to assess IAQ in academic buildings. Using microcontrollers and sensors, it measured temperature, humidity, pressure, CO_2, CO, and PM2.5. AI processing enabled efficient data handling, achieving reliable prediction accuracy. Average values were 30 °C, 42% RH, 100,422 Pa, 460 ppm CO_2, 2.2 ppm CO, and 15.3 µg/m³

PM2.5. The system proved effective in forecasting and managing IAQ, enhancing safety and comfort in educational settings.

- ***Fernandes and Gonçalves [23], (2023),*** suggested a bidirectional LSTM model for IAQ prediction, focusing on forecasting pollutant levels due to their critical impact on public health. The model was applied to short- and long-term forecasting tasks, achieving RMSE of 8.703 and MAE of 2.892 for one-minute predictions, and RMSE of 53.791 and MAE of 16.193 for one-hour predictions. The results demonstrated that the bidirectional approach outperformed traditional models, confirming its effectiveness for accurate IAQ forecasting.
- ***E. Gunawan et al. [24], (2023),*** proposed a DL framework based on multivariate time-series data for predicting temperature and relative humidity in enclosed environments. The model achieved near-perfect accuracy ($R^2 > 0.99$) on real datasets, confirming the effectiveness of DL methods for environmental prediction and their value in agriculture and facility management.
- ***Drikakis et al. [25], (2024),*** focused on DL techniques, specifically an LSTM model. The study analyzed the impact of limited and aggregated data on LSTM-based temperature and humidity predictions in ventilated environments, showing that while forecasts remained reliable, data scarcity and airflow dynamics significantly affected accuracy.
- ***Zhu et al. [26], (2024),*** proposed a hybrid CNN-BiLSTM model enhanced with Adaptive Particle Swarm Optimization (APSO) for air quality prediction. Applied to AQI time-series data from monitoring stations in Xi'an, China, the model dynamically optimized hyperparameters and achieved superior performance over baseline methods, with RMSE of 38.93 and MAE of 29.19. The results confirmed

the effectiveness of optimization-based hybrid architectures for spatial-temporal environmental forecasting.

- ***Spyrou et al. [27], (2024),*** focused on developing a classification tool for IAQ management with a focus on explaining ability. The study applied k-means clustering and a Random Forest model on a public dataset for IAQ classification, added an IAQ Index, and developed a Python web tool with SHAP plots to improve interpretability and support IAQ management.
- ***Kutala et al. [28], (2024),*** focused on a hybrid DL–based framework for air pollution prediction and AQI classification, introducing the BSSO-HDL model that integrates Binary Spring Search Optimization with hybrid DL techniques. The CNN-ELM model with BSSO hyperparameter tuning achieved superior air quality prediction during COVID-19, outperforming XGBoost, SVM, and RF, with $R^2 = 0.922$, RMSE = 15.422, and MAE = 10.029.
- ***Wang et al. [29], (2024),*** proposed a lightweight air quality monitoring framework using a multiscale dilated CNN designed for mobile and IoT edge devices. The model used dilated kernels and multiscale feature fusion, reducing parameters by 86.7% and FLOPs by 88.5%, achieving 94.2% Top-1 accuracy and enabling efficient air quality mapping on resource-constrained IoT devices.

Table (1.1): Approaches used in previous works.

No.	Authors, Ref., Year	Deep learning model	Datasets	The main advantages	The main Disadvantages
1	Shi et al. [11], 2018	Improved BP Neural Network	Chongqing Cloud Database for Industrial Data.	Very accurate predictions of indoor temperature and relative humidity	Poor performance for the long-term relative humidity forecast.
2	Xu et al. [12],2018	LSTM + Error Correction Model	Indoor temperature dataset, office building, China	High level of accuracy in trend and direction predictions-D-stat ~ 98%	Limitation of the size of data; fairly better than other ML models
3	Zhao, X.; Zhang, R. [13], 2018	Recurrent Neural Network	Air quality data from US EPA (CO, NO2, O3, SO2, PM2.5, PM10)	Good at processing sequential data with memory capabilities, superior to SVM and Random Forest in performance	Limited to sequential data and may require extensive historical data for optimal performance
4	Jin et al. [14], 2019	Regression & Classification Models	Smart Home Benchmark Dataset	High precision around 0.13°C MAE; it can support real-time personalized control.	Limited to some smart home platforms
5	Parashar and Sonker [15], 2019	DNN with Hyperparameter Optimization (Talos)	Air quality data with pollutants PM10, PM2.5, SO2, NO2	Hyperparameter optimization improves the prediction accuracy and handles model tuning effectively	Relies on a trial-and-error approach in traditional methods without optimization
6	Elmaz et al. [16], 2021	CNN-LSTM	The dataset provided by Building Z, University of Antwerp	High accuracy in the short- and medium-term forecast: $R^2 > 0.9$	Long-term deterioration of performance due to accumulated estimation error

7	Eka et al. [17], 2022	Seq2Seq (LSTM and GRU)	Room Climate Dataset (273,144 timestamps)	Better accuracy compared to the baseline models (MAE: LSTM ~0.00941, GRU ~0.03013); suitable for sequence-to-sequence tasks.	The seq2seq model overfits; better hyperparameters and pre-processing are needed.
8	Hou et al. [18], 2022	CNN-LSTM	60,133 hourly meteorological data (air temperature, dew point, air pressure, wind direction, wind speed, and cloud amount) from Yinchuan, China (2000-2020)	High accuracy: MAE 1.02 and R^2 0.7258; extracts features using a CNN with LSTM to capture long-term memory.	Computationally more expensive compared to a single CNN or single LSTM; slightly more difficult to train and fine-tune
9	Ozbek et al. [19], 2022	LSTM, ANFIS with Fuzzy C-Means (FCM)	Daily relative humidity data (2012-2019) from six provinces in Turkey	Precise short-term prediction, particularly under desertic weather conditions of Diyarbakir; LSTM avoids the vanishing gradient problem	ANFIS does need parameter tuning, while LSTM may overfit in small datasets.
10	Bao et al. [20], 2022	FL-CNN-LSTM	IAQ data - CO_2, PM10, PM2.5, VOC, Temperature, etc., Shanghai, Nov. 2016-March 2017	High accuracy for multi-step IAQ prediction, with integration of fuzzy logic for interpretability.	Demands extensive computational pre-processing and fine-tuning of fuzzy logic to achieve optimal outcomes.
11	Di Già and Papurello [21], 2022	LSTM Neural Network	Indoor temperature and HVAC data of 15 offices in the	Accurate multi-horizon temperature prediction	Needs heavy adaptation; heavy architecture might cause

			Energy Center, Turin, Italy (2019-2020)	(RMSE ~0.1°C); robust for various time horizons (2h-24h)	overfitting if not appropriately regularized.
12	Marzouk, M.and Atef, M. [22], 2022	DL (IoT integration for IAQ)	IAQ data from IoT sensors	Effective in real-time prediction and managing IAQ, with low disruption in data transfer	Complex system design depends on IoT infrastructure.
13	Fernandes and Gonçalves [23], 2023	Bidirectional LSTM (BiLSTM)	IAQ measured by GAMS; 135,099 entries ranging from CO_2, PM10, PM2.5, VOC, temperature, and humidity.	Accurate multi-output predictions, at 8.703 RMSE for a 1-minute forecast; handle multivariate time series.	Struggles with extremely high or sudden data spikes, computationally heavier than the usual LSTM.
14	E. Gunawan et al. [24], 2023	Transformer, Transformer LPE, LSTM, GRU	Room Climate Dataset Building 3	High accuracy of prediction: $R^2 > 0.99$. Performance robustness was checked in all models using multivariate inputs.	Transformer models are quite computationally expensive. Both GRU and LSTM necessitate tuning to avoid overfitting.
15	Drikakis et al. [25], 2024	LSTM	High-resolution flow simulation data of temperature, velocity, and relative humidity in a rectangular room	High accuracy in predicting temperature and humidity under sparse data conditions; handles long-term dependencies effectively	Reduced accuracy with high data sparsity; requires significant computational resources for training.
16	Zhu et al. [26], 2024	APSO-CNN-BiLSTM	Air Quality & Meteorological data from Xi'an, China	APSO improves hyperparameter tuning dynamically - Combines spatial and	Focused only on prediction, not classification - Requires more computation due

				temporal learning via CNN + BiLSTM	to the optimization loop - No deployment interface or real-time framework included
17	Spyrou, E. D.and Kappatos, V. [27], 2024	Random Forest with K-means Clustering (SHAP)	IAQ dataset with k-means clustering	Provides high classification accuracy and explainability via SHA	Limited by data availability and the need for interpretability tools for non-experts
18	Kutala et al. [28], 2024	Convolutional Neural Network with Extreme Learning Machine (CNN-ELM) and BSSO	Air pollution data during the COVID-19 lockdown	Optimized with hyperparameter tuning to improve prediction performance, effective in AQI forecasting	Complex model setup with pre-processing and hyperparameter optimization can be computationally intensive.
19	Wang et al. [29], 2024	Multiscale Dilated CNN (MDNet)	GAOs-2 dataset (1054 labeled air quality images)	Achieves high accuracy (94.2%) with significantly reduced parameters (86.7%) and FLOPs (88.5%), making it suitable for mobile and IoT	Limited generalizability to other geographical locations without fine-tuning or retraining

Both Bao et al. (2022) and Elmaz et al. (2021) examine indoor environmental prediction using hybrid DL models. These models combine CNNs for spatial feature extraction with LSTMs to capture temporal dependencies. Similar to this dissertation, their approaches rely on sensor-based data and demonstrate superior performance compared to baseline models.

However, the two studies differ in both scope and methodology. Bao et al. incorporated fuzzy logic to enhance interpretability and address uncertainty in IAQ prediction, utilizing PM2.5 data collected over several months in Shanghai. In contrast, Elmaz et al. applied a 1DCNN-LSTM framework specifically for short-term indoor temperature forecasting in HVAC systems, with a prediction horizon of up to 120 minutes.

This dissertation extends beyond both works by targeting multiple IAQ variables (CO_2, PM2.5, temperature, humidity) in healthcare and educational buildings. It focuses on long-term forecasting and system optimization for the practical management of SBS.

1.3 Problem Statement

The rapid growth of modern construction in Iraq, influenced by climatic factors and weak architectural design with poor ventilation, has intensified IAQ challenges and the risk of SBS, particularly in healthcare facilities. However, datasets related to SBS in Iraq are scarce, inconsistent, and non-standardized, reducing the reliability of DL models [30].

Existing monitoring practices still rely on manual inspections and surveys, which are slow, error-prone, and lack real-time responsiveness. The absence of automated AI- and IoT-based systems further delays corrective action and increases health risks [31].

DL models also require high computational resources, making large-scale deployment difficult in resource-limited settings such as Iraq [32]. Although lightweight models and optimization techniques offer promising alternatives, infrastructure constraints, including limited sensor networks, unstable connectivity, and outdated monitoring systems, still hinder effective IAQ management, with reports confirming insufficient monitoring coverage nationwide [33].

Poor IAQ is directly linked to respiratory diseases, cognitive decline, and reduced workplace performance. In healthcare environments, inadequate ventilation and elevated pollutants exacerbate airborne disease transmission. Recent studies have shown pollutant concentrations exceeding WHO standards, underscoring the urgent need for AI-driven predictive systems to protect health and improve IAQ management in Iraq [34].

1.4 Aim and Objectives of the Dissertation

The primary aim of this dissertation is to design an optimized DL framework for the detection of SBS and the prediction of environmental conditions in healthcare settings, To achieve this aim, the following objectives were pursued:

1. Create a novel IAQ dataset by developing a custom Arduino-based monitoring system integrating multiple sensors (CO_2, TVOC, PM2.5, PM10, CO, O_3, AQ, LDR, temperature, and relative humidity). The dataset was continuously collected for eight months from hospital wards, providing the first structured SBS-related dataset in Iraq.
2. Applying preprocessing and data preparation steps to ensure it is ready for classification and forecasting tasks.

3. Apply advanced deep learning methods (e.g., DNN, LSTM, and hybrid 1D-CNN-BiLSTM) for SBS detection and environmental prediction, optimized with NAS, PL, and SVD to enhance efficiency and accuracy.
4. Build forecasting models for key IAQ parameters, particularly temperature and relative humidity, using the proposed DL framework.
5. Evaluate the performance of the proposed models using standard classification and regression metrics, including accuracy, precision, recall, F1-score, and computational efficiency.

1.5 Contribution

This dissertation aims to advance IAQ monitoring and environmental condition prediction in healthcare facilities, with Baqubah Teaching Hospital in Iraq as the case study. The research focuses on improving IAQ classification and forecasting of key parameters, particularly temperature and relative humidity, through the development of a predictive DL framework. By combining IAQ assessments with short-term environmental predictions, the study supports both occupant health and the effective functioning of healthcare environments. The main contributions of this dissertation are as follows:

1. New Dataset Creation: Developed the first structured IAQ dataset in Iraq (523,524 samples) using a custom Arduino-based multi-sensor system, continuously collected from male and female wards.
2. Building DL Model: Built and benchmarked DL models for IAQ classification and forecasting of temperature and humidity (up to 60 minutes ahead) using a sliding window approach, with the hybrid 1D-CNN-BiLSTM achieving superior performance.
3. Optimization: Applied three optimization techniques (NAS, PL, and SVD/LRF) to reduce model complexity and inference time while

maintaining high predictive accuracy (classification accuracy up to 94.8%, $R^2 > 0.99$ for forecasting).

4. Integration & Practical Impact: Integrated IAQ methods with AI-driven analytics to support early SBS detection and proactive environmental management, providing a lightweight and efficient framework for real-world deployment in healthcare facilities.

1.6 Scope and Limitation

1.6.1 Stady scope

The primary objective of this dissertation is to develop a deep learning model capable of detecting SBS through the classification of IAQ. The model is trained on real environmental data collected from Baqubah Teaching Hospital in Iraq. The research focuses on employing a hybrid 1D-CNN-BiLSTM architecture, optimized using NAS, PL, and LRF. Furthermore, the scope of this work includes the development of an integrated system with an interactive GUI designed to display classification results and provide health-related recommendations, enabling practical deployment in healthcare environments.

1.6.2 Stady Limitations

Despite the significant contributions of this work, several limitations should be acknowledged. First, the dataset was collected from a single case study (Baqubah Teaching Hospital), which may limit the generalizability of the findings to other healthcare settings or geographic regions. In addition, environmental conditions were measured only in selected wards (male and female), not across all hospital departments. The forecasting framework was restricted to short-term predictions (up to 60 minutes ahead) and was limited to temperature and humidity rather than the full set of IAQ parameters. To address class imbalance, duplication-based oversampling was applied, which may not fully capture the complexity of real-world IAQ variations. Finally, the hardware implementation was based on Arduino Mega, which may present scalability challenges when applied to larger or more complex systems.

1.7 Dissertation Structure

The dissertation is structured in five chapters; here, a brief description of their contents is given:

Chapter two: Presents the theoretical background for the utilized techniques to classify IAQ and prediction by temperature and Relative Humidity, as well as the advantages and disadvantages of using each type of these techniques.

Chapter Three: Illustrate the methodology of the proposed models.

Chapter Four: Describes the experiments that are conducted to evaluate the proposed systems and validate the hypothesis of this work, in addition to the results collected from these experiments.

Chapter Five: Discusses results, conclusions, and lists some suggestions for future studies