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USER INTERFACE DESIGN FOR A ZOONOSIS PREDICTION SYSTEM

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Abstract

Zoonosis is any diseases that are transmitted from animal to human. The high-risk impact on zoonosis is increasing since we live in the same environment with some animals. There is important to enhance our attentions to resolve this kind problem. Previously, zoonosis prediction framework has been proposed. This framework was able to predict the number of human incidence of seasonal zoonosis. However, it still needs to transform the framework into a user-friendly user interface. This study examined concerns about the construction of user interface application of zoonosis prediction framework. The results demonstrate decision support system (DSS) architecture. The design covers three DSS components, namely database management subsystem, model base management subsystem, and user interface subsystem. Spreadsheet DSS was applied for the zoonosis prediction application. The model was developed by using the VBA for Excel. In conclusion, the finding determines that the interface can integrate three DSS components in a single DSS interface.

Keywords: User Interface, Decision Support System, Prediction, Zoonosis.

1. Introduction

It is an estimation that around 75% of infectious diseases in human come from an animal. Commonly, vertebrae animals can transmit a disease to human and vice-versa [1]. These diseases are classified as zoonosis.

Abbreviations

ANOVA	Analysis of Variance
ARIMA	Autoregressive Integrated Moving Average
CV	Coefficient of Variance
DBMS	Database Management Systems
DSS	Decision Support System
GUI	Graphical User Interface
MBMS	Model Base Management Systems
VBA	Visual Basic for Application

The arising threats of zoonosis incidence require special attention since there is interaction between human and animal in the same environment. Different approaches have been conducted to overcome this problem, one of them through information technology. It was reported by Smith et al. that more than 44 million cases took place in 219 nations [2]. Recently, more zoonosis cases in human are emerged, including Zika virus [3], Yellow fever in Brazil that resulted travel notice to epidemics country [4], and Seoul Virus [5]. There is a need to propose a decision support system for zoonosis prediction. This kind of system provided an interesting insight into the nature of system development which able to forecast a number of zoonosis incidence in human.

The concept of Decision Support System (DSS) is very broad because of the many diverse approaches and a wide range of domains in which decisions are made. Power [6] wrote that research on DSS started in the1960s with the development of a model-driven system. It was followed by the development of theory in the 1970s, and then the application of financial planning, spreadsheet DSS and Group DSS (GDSS) in the 1980s. Turban defines DSS as an approach (or methodology) for supporting decision-making [7].

DSS [8] also can be defined as a system under the control of one or more decision makers that assists in the activity of decision making by providing an organized set of tools intended to impart structure to portions of the decision-making situation and to improve the ultimate effectiveness of the decision of the outcome. In general, DSS is a computerized system that can assist the user in making decisions, including in medical field.

Considering the zoonosis matter, some researchers have conducted a different study of zoonosis prediction. Nandini et al. developed GUI for predicting Dengue. The GUI separated two panels which were for researchers and regular users. Researcher entered data onto the training set, while the users might get the prediction from the system [9]. Global Early Warning System (GLEWS) emphasized vector-environment relationships and potentially predict the risk of disease outbreaks or epidemics in India using GIS technology [10].

A mathematical approach has the opportunity to predict zoonotic diseases pandemic [11, 12]. A recent zoonotic disease outbreak motivates numerous researchers to develop a system prediction, for example Salmonellosis [13], Zika [13-15], Middle East Respiratory Syndrome Coronavirus (MERS-CoV) [16, 17], Avian Influenza A (H7N9) [18-20], Rift Valley Fever [21, 22], and Chikungunya [23-25].

However, some existing emerging zoonosis systems have been derived from one method and focus on specific disease. Due to the numerous available forecasting method, this paper considered six forecasting techniques. Further, the framework is also can be implemented into various zoonotic diseases.

A previous DSS framework for seasonal zoonosis prediction was proposed by Permanasari et al. [26]. It focused on the forecasting of human cases from seasonal zoonosis. Terminology 'seasonal' mean that disease number of incidence exhibited the seasonal pattern. Furthermore, it is important to develop a decision support system graphical user interface (GUI) that provide the feature of the framework. It eases user to access system and get results from data input.

This paper provided an interesting insight into the nature of GUI development to forecast a number of zoonosis incidence in human. In particular, it only focused on the seasonal zoonosis incidence. The remainder of the paper is structured as follows. Section 2 introduces a zoonosis prediction framework. Section 3 presents methodology. Section 4 reports the results of user interface subsystem and system evaluation. Finally, Section 5 presents the conclusion of the study.

2. Zoonosis Prediction Framework

The previous work by Permanasari et al. proposed a seasonal zoonosis prediction framework [26]. The system framework was able to predict the future number of seasonal zoonosis occurrences. It integrated various resources of information and providing relevant knowledge.

The framework is divided into three DSS components as illustrated in Fig. 1.

a. Database management subsystem

This subsystem is consists of zoonosis database that is collected from zoonosis incidence in human in United State for the 168 month period from January 1993 to December 2006 (Salmonellosis).

b. Model base management subsystem

This component transforms data from database management system into information for decision making. Six different forecasting results were developed in this subsystem (regression, moving average, decomposition, Holt-Winter's, ARIMA, and neural network).

c. User interface subsystem

The purpose of this component is to design interaction media between the user and the model. The user may input different data and get a result corresponding to the input value. What-if analysis (sensitivity analysis) was chosen to model the user interface system.

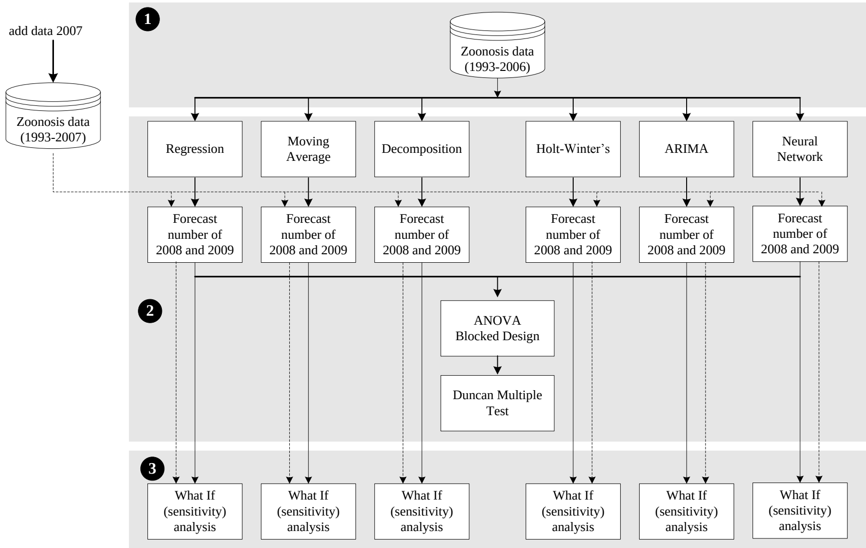


Fig. 1. Zoonosis prediction DSS [5].

3. Methods

The application of the proposed framework came out with GUI design that was a representation of three DSS components into a user-friendly interface. The user can access the system through this interface. The zoonosis GUI was designed using spreadsheet-based DSS. This section describes the logic used to create Excel Visual Basic for Application (VBA) model and also includes the different worksheets. VBA for modelers intends the feature of Excel which can be extended to provide application front end based spreadsheet [27]. This tool simplifies spreadsheets transformation into GUI. It also explains the interface that integrates 3 DSS components in a single DSS interface.

Figure 2 illustrates the flow of DSS GUI based on the proposed framework. The GUI is opened by “Welcome” form. It is followed by “Process Selection” form. Through this form, three DSS components are presented and can be selected by the user. As seen in Fig. 2, different software is used for processing forecasting results for each method within the MBMS component. Then, the results are copied into the excel sheet to be further processed.

Using several available methods, there is the possibility of selecting the most appropriate method that produces the better results. Besides the forecasting method, the changes in the time series may yield the different results. It was shown by sensitivity analysis results. Using this analysis, the user could identify the result fluctuations in the different method. The results provided the user which forecasting method was more stable based on data updated. Couple with ANOVA, Duncan Test and CV results, the user could choose appropriate method that having the smallest variation and relatively produced little fluctuation triggered by the changing of data.

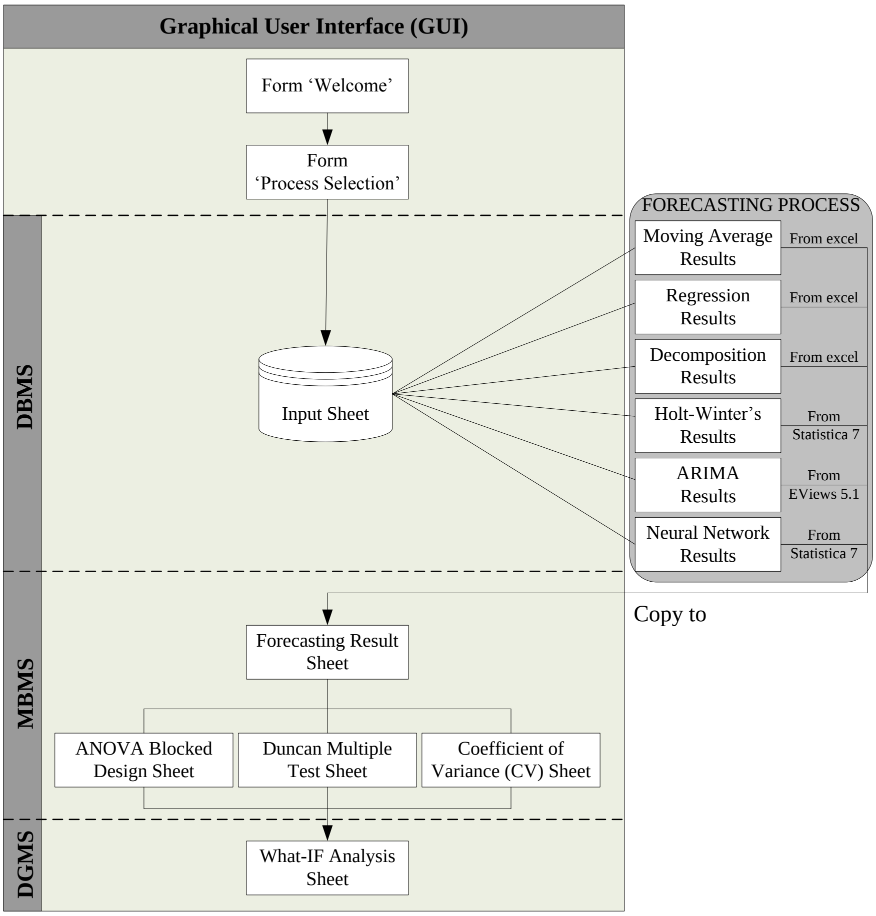


Fig. 2. GUI Flow of the proposed framework.

4. Results and Discussion

4.1. Graphical user interface

The application is opened by “Welcome” form as seen in Fig. 3. This form consists of two command button, namely “About” and “ENTER”. Button “About” display application description), while when user click button “ENTER” then it open the application by selection of process in Fig. 4.

User form “Process Selection” (Fig. 4) is divided into two parts, drop down box for disease selection and frame “Process” for process selection. Using “Process” users can choose which component of DSS will be processed. There are three radio buttons to represents each DSS component: “Modify Data” for DBMS, “Display Forecasting” for MBMS and “Display What-If Analysis for DGMS. Within this form, the user can also add more disease using command button “Add Disease”. In Fig. 4, Salmonellosis is chosen as the case study for the following interfaces.

Fig. 3. Welcome form.

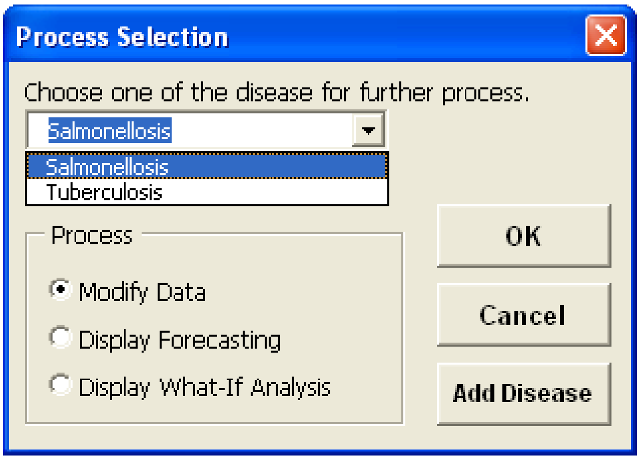


Fig. 4. Process selection form.

Spreadsheet DSS was applied for the zoonosis prediction application. Therefore, there are several sheets in DSS application. Figure 5 shows input sheets for Salmonellosis dataset. Input table is divided into three columns: t, Month, and No of Incidence. Input spreadsheet is completed by 3 command button: Continue (for next process), Return to Process Selection (for back to Process Selection form in Fig. 5), and End (for closing the sheet). Once data are entered into the sheet, forecasting results can be calculated. The data are processed through different tools and results for each method are copied into Forecasting Results sheet as seen in Fig. 6.

The actual data and forecasting results are presented in this sheet, where the user can select from the list of the command button to display a specific chart. If the user selects the first option, then the chart is shown graphically as in Fig. 7 and the selection of the last option illustrate the chart in Fig. 8. In each chart, there is a command button "View Forecasting Sheet" that allow the user for back to forecasting results sheet.

Figure 6 represents the process in the MBMS component where beside the radio button list, it is also provided others calculation in the MBMS, including ANOVA, Duncan Multiple Range Test, and CV. The process can be accessed through the respective command button. When the user clicks the buttons, "ANOVA Result" (Fig. 9), "Duncan Multiple Range Test Result" (Fig. 10), and "Coefficient of Variance" (Fig. 11) are displayed sequentially.

When users have finished the process in the MBMS, they can back to the "Process Selection" form to continue accessing other processes. The last option is "Display What-If Analysis". The interface of this process is showed in Fig. 12. The interface contains several buttons for navigating to the various chart sheets. The example of the first chart can be seen in Fig. 13.

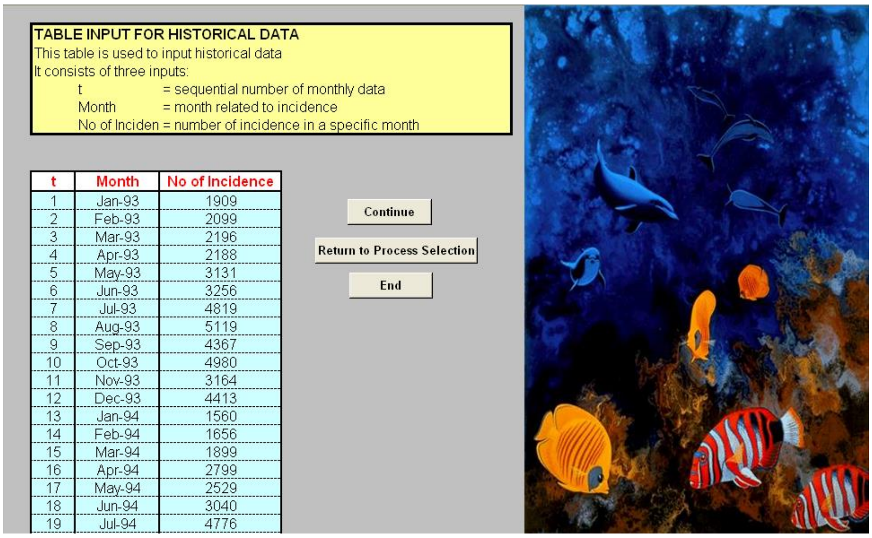
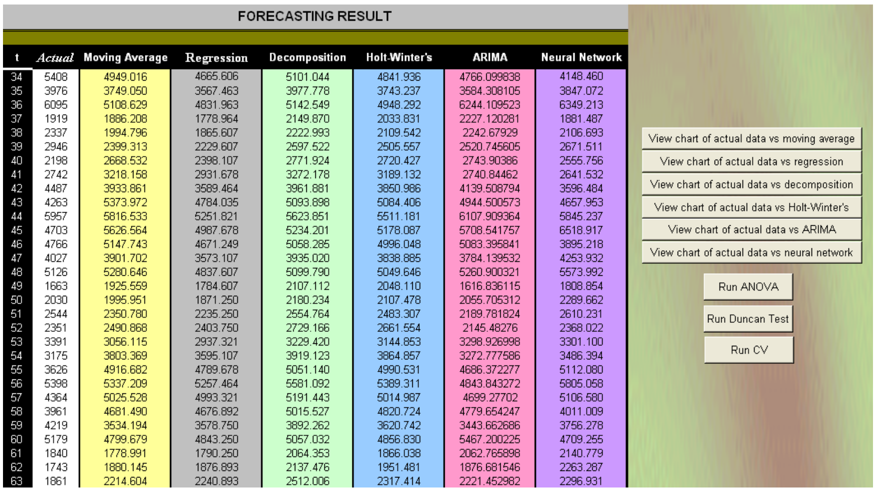


TABLE INPUT FOR HISTORICAL DATA
This table is used to input historical data
It consists of three inputs:
t = sequential number of monthly data
Month = month related to incidence
No of Inciden = number of incidence in a specific month

t	Month	No of Incidence
1	Jan-93	1909
2	Feb-93	2099
3	Mar-93	2196
4	Apr-93	2188
5	May-93	3131
6	Jun-93	3256
7	Jul-93	4819
8	Aug-93	5119
9	Sep-93	4367
10	Oct-93	4980
11	Nov-93	3164
12	Dec-93	4413
13	Jan-94	1560
14	Feb-94	1656
15	Mar-94	1899
16	Apr-94	2799
17	May-94	2529
18	Jun-94	3040
19	Jul-94	4776

Fig. 5. Input table.


FORECASTING RESULT

t	*Actual*	Moving Average	Regression	Decomposition	Holt-Winter's	ARIMA	Neural Network
34	5408	4949.016	4665.606	5101.044	4841.936	4766.099838	4148.460
35	3976	3749.050	3567.463	3977.778	3743.237	3584.308105	3847.072
36	6095	5108.629	4831.963	5142.549	4948.292	6244.109523	6349.213
37	1919	1886.208	1778.964	2149.870	2033.831	2227.120281	1881.487
38	2337	1994.796	1865.607	2222.993	2109.542	2242.67929	2106.693
39	2946	2399.313	2229.607	2597.522	2505.557	2520.745605	2671.511
40	2198	2668.532	2398.107	2771.924	2720.427	2743.90386	2555.756
41	2742	3218.158	2931.678	3272.178	3189.132	2740.84462	2641.532
42	4487	3933.861	3589.464	3961.881	3850.986	4139.508794	3596.484
43	4263	5373.972	4784.035	5093.898	5084.406	4944.500573	4657.953
44	5957	5816.533	5251.821	5623.851	5511.181	6107.909364	5845.237
45	4703	5626.564	4987.678	5234.201	5178.087	5708.541757	6518.917
46	4766	5147.743	4671.249	5058.285	4996.048	5083.395841	3895.218
47	4027	3901.702	3573.107	3935.020	3838.885	3784.139532	4253.932
48	5126	5280.646	4837.607	5099.790	5049.646	5260.900321	5573.992
49	1663	1925.559	1784.607	2107.112	2048.110	1616.836115	1808.854
50	2030	1995.951	1871.250	2180.234	2107.478	2055.705312	2289.662
51	2544	2350.780	2235.250	2554.764	2483.307	2189.781824	2610.231
52	2351	2490.868	2403.750	2729.166	2661.554	2145.48276	2368.022
53	3391	3056.115	2937.321	3229.420	3144.853	3298.926998	3301.100
54	3175	3803.369	3595.107	3919.123	3864.857	3272.777586	3486.394
55	3626	4916.682	4789.678	5051.140	4990.531	4686.372277	5112.080
56	5398	5337.209	5257.464	5581.092	5389.311	4843.843272	5805.058
57	4364	5025.528	4993.321	5191.443	5014.987	4699.27702	5106.580
58	3961	4681.490	4676.892	5015.527	4820.724	4779.654247	4011.009
59	4219	3534.194	3578.750	3892.262	3620.742	3443.662686	3756.278
60	5179	4799.679	4843.250	5057.032	4856.830	5467.200225	4709.255
61	1840	1778.991	1790.250	2064.353	1866.038	2062.765898	2140.779
62	1743	1880.145	1876.893	2137.476	1951.481	1876.681546	2263.287
63	1861	2214.604	2240.893	2512.006	2317.414	2221.452982	2296.931

Fig. 6. Forecasting results sheet.

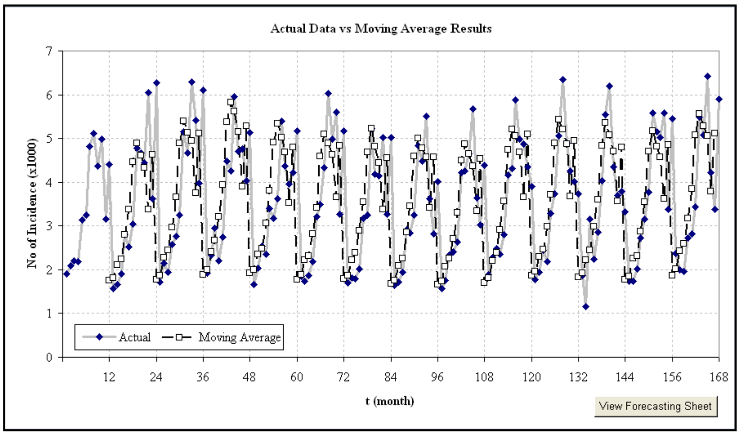


Fig. 7. Actual data vs. moving average chart.

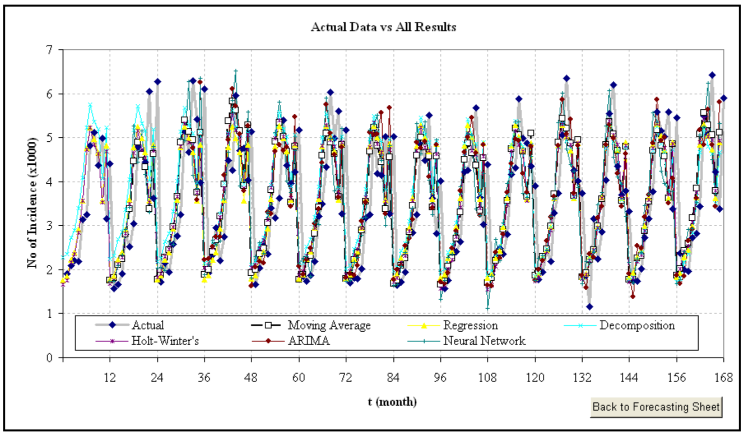
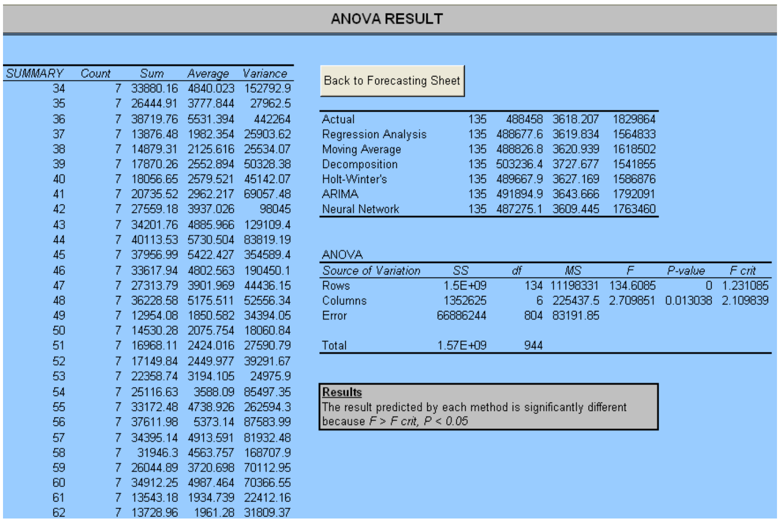


Fig. 8. Actual data vs. all results chart.



ANOVA RESULT

SUMMARY	Count	Sum	Average	Variance
34	7	33880.16	4840.023	152792.9
35	7	26444.91	3777.844	27962.5
36	7	38719.76	5531.394	442264
37	7	13876.48	1982.354	25903.62
38	7	14879.31	2125.616	25534.07
39	7	17870.26	2552.894	50328.38
40	7	18056.65	2579.521	45142.07
41	7	20735.52	2962.217	69057.48
42	7	27559.18	3937.026	98045
43	7	34201.76	4885.966	129109.4
44	7	40113.53	5730.504	83819.19
45	7	37956.99	5422.427	354589.4
46	7	33617.94	4802.563	190450.1
47	7	27313.79	3901.969	44436.15
48	7	36228.58	5175.511	52556.34
49	7	12954.08	1850.582	34394.05
50	7	14530.28	2075.754	18060.84
51	7	16968.11	2424.016	27590.79
52	7	17149.84	2449.977	39291.67
53	7	22358.74	3194.105	24975.9
54	7	25116.63	3588.09	85497.35
55	7	33172.48	4738.926	262594.3
56	7	37611.98	5373.14	87583.99
57	7	34395.14	4913.591	81932.48
58	7	31946.3	4563.757	168707.9
59	7	26044.89	3720.698	70112.95
60	7	34912.25	4987.464	70366.55
61	7	13543.18	1934.739	22412.16
62	7	13728.96	1961.28	31809.37

Back to Forecasting Sheet

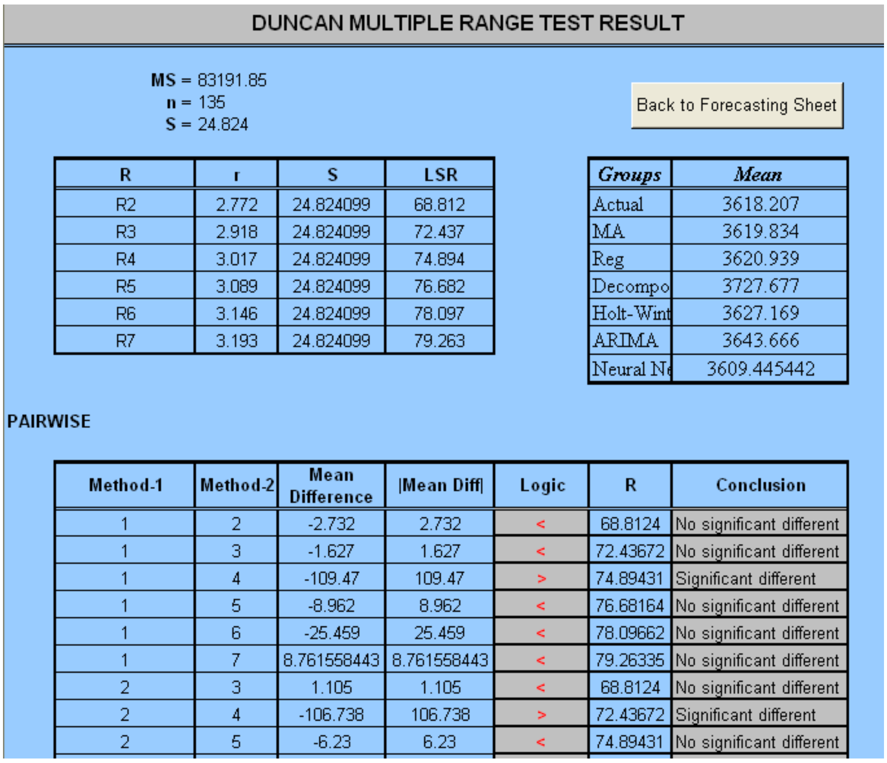
Actual	135	488458	3618.207	1829864
Regression Analysis	135	488677.6	3619.834	1564833
Moving Average	135	488826.8	3620.939	1618502
Decomposition	135	503236.4	3727.677	1541855
Holt-Winter's	135	489667.9	3627.169	1586876
ARIMA	135	491894.9	3643.666	1792091
Neural Network	135	487275.1	3609.445	1763460

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Rows	1.5E+09	134	11198331	134.6085	0	1.231085
Columns	1352625	6	225437.5	2.709851	0.013038	2.109839
Error	66886244	804	83191.85			
Total	1.57E+09	944				

Results
The result predicted by each method is significantly different because *F > F crit, P < 0.05*

Fig. 9. ANOVA result.



DUNCAN MULTIPLE RANGE TEST RESULT

MS = 83191.85
n = 135
S = 24.824

Back to Forecasting Sheet

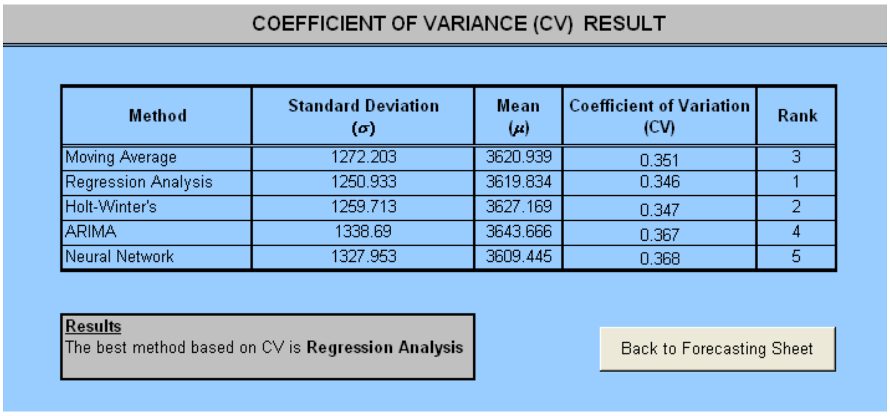
R	r	S	LSR
R2	2.772	24.824099	68.812
R3	2.918	24.824099	72.437
R4	3.017	24.824099	74.894
R5	3.089	24.824099	76.682
R6	3.146	24.824099	78.097
R7	3.193	24.824099	79.263

Groups	*Mean*
Actual	3618.207
MA	3619.834
Reg	3620.939
Decompo	3727.677
Holt-Wint	3627.169
ARIMA	3643.666
Neural Ne	3609.445442

PAIRWISE

Method-1	Method-2	Mean Difference	|Mean Diff|	Logic	R	Conclusion
1	2	-2.732	2.732	<	68.8124	No significant different
1	3	-1.627	1.627	<	72.43672	No significant different
1	4	-109.47	109.47	>	74.89431	Significant different
1	5	-8.962	8.962	<	76.68164	No significant different
1	6	-25.459	25.459	<	78.09662	No significant different
1	7	8.761558443	8.761558443	<	79.26335	No significant different
2	3	1.105	1.105	<	68.8124	No significant different
2	4	-106.738	106.738	>	72.43672	Significant different
2	5	-6.23	6.23	<	74.89431	No significant different

Fig. 10. Duncan results.



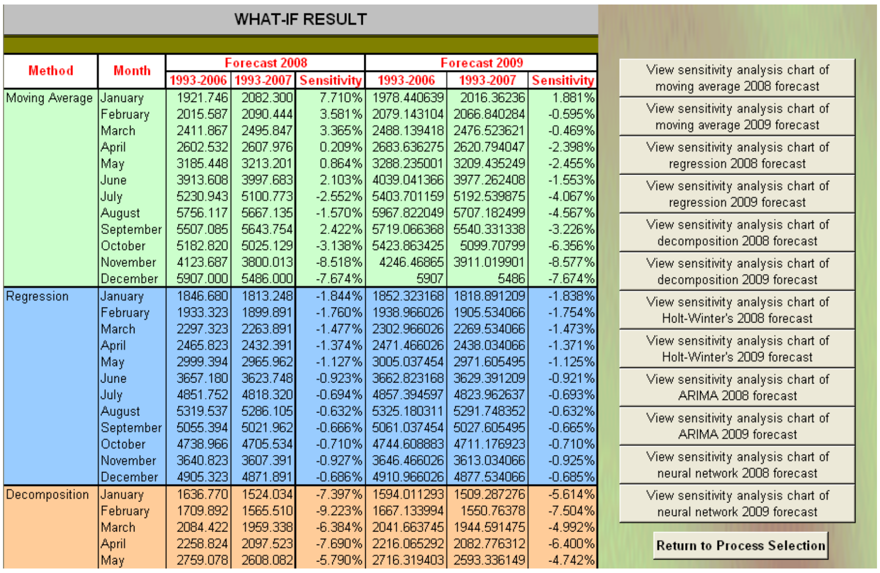
COEFFICIENT OF VARIANCE (CV) RESULT

Method	Standard Deviation (σ)	Mean (μ)	Coefficient of Variation (CV)	Rank
Moving Average	1272.203	3620.939	0.351	3
Regression Analysis	1250.933	3619.834	0.346	1
Holt-Winter's	1259.713	3627.169	0.347	2
ARIMA	1338.69	3643.666	0.367	4
Neural Network	1327.953	3609.445	0.368	5

Results
The best method based on CV is **Regression Analysis**

Back to Forecasting Sheet

Fig. 11. Coefficient of variance result.



WHAT-IF RESULT

Method	Month	Forecast 2008			Forecast 2009		
		1993-2006	1993-2007	Sensitivity	1993-2006	1993-2007	Sensitivity
Moving Average	January	1921.746	2082.300	7.710%	1978.440639	2016.36236	1.881%
	February	2015.587	2090.444	3.581%	2079.143104	2066.840284	-0.595%
	March	2411.867	2495.847	3.365%	2488.139418	2476.523621	-0.469%
	April	2602.532	2607.976	0.209%	2683.636275	2620.794047	-2.398%
	May	3185.448	3213.201	0.864%	3288.235001	3209.435249	-2.455%
	June	3913.608	3997.683	2.103%	4039.041366	3977.262408	-1.553%
	July	5230.943	5100.773	-2.552%	5403.701159	5192.539875	-4.067%
	August	5756.117	5667.135	-1.570%	5967.822049	5707.182499	-4.567%
	September	5507.085	5643.754	2.422%	5719.066368	5540.331338	-3.226%
	October	5182.820	5025.129	-3.138%	5423.863425	5099.70799	-6.356%
	November	4123.687	3800.013	-8.518%	4246.46865	3911.019901	-8.577%
	December	5907.000	5486.000	-7.674%	5907	5486	-7.674%
Regression	January	1846.680	1813.248	-1.844%	1852.323168	1818.891209	-1.838%
	February	1933.323	1899.891	-1.760%	1938.966026	1905.534066	-1.754%
	March	2297.323	2263.891	-1.477%	2302.966026	2269.534066	-1.473%
	April	2465.823	2432.391	-1.374%	2471.466026	2438.034066	-1.371%
	May	2999.394	2965.962	-1.127%	3005.037454	2971.605495	-1.125%
	June	3657.180	3623.748	-0.923%	3662.823168	3629.391209	-0.921%
	July	4851.752	4818.320	-0.694%	4857.394597	4823.962637	-0.693%
	August	5319.537	5286.105	-0.632%	5325.180311	5291.748352	-0.632%
	September	5055.394	5021.962	-0.666%	5061.037454	5027.605495	-0.665%
	October	4738.966	4705.534	-0.710%	4744.608883	4711.176923	-0.710%
	November	3640.823	3607.391	-0.927%	3646.466026	3613.034066	-0.925%
	December	4905.323	4871.891	-0.686%	4910.966026	4877.534066	-0.685%
Decomposition	January	1636.770	1524.034	-7.397%	1594.011293	1509.287276	-5.614%
	February	1709.892	1565.510	-9.223%	1667.133994	1550.76378	-7.504%
	March	2084.422	1959.338	-6.384%	2041.663745	1944.591475	-4.992%
	April	2258.824	2097.523	-7.690%	2216.065292	2082.776312	-6.400%
	May	2759.078	2608.082	-5.790%	2716.319403	2593.336149	-4.742%

Fig. 12. What-if result.

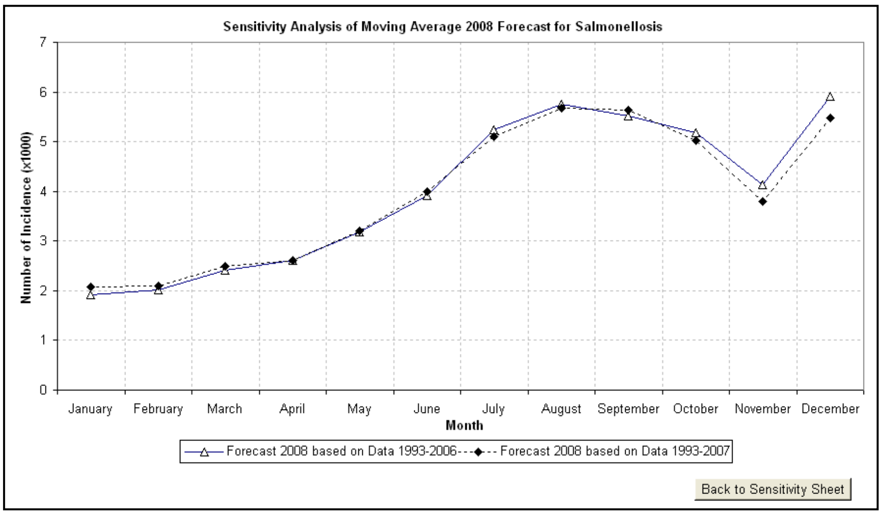


Fig. 13. Example chart of sensitivity analysis forecast results.

4.2. System Evaluation

Within system evaluation, two different approaches were conducted, namely Black Box Testing and User Evaluation Testing.

4.2.1. Black box testing

The component of the user interface was evaluated by using Black Box method. Its method focuses on analyzing of software functional requirement [28]. Table 1 provides results of Black Box Testing. It defines numerous zoonosis GUI feature and indicates that system functionality fit the expected results. Therefore, a system performance is acceptable.

Table 1. Black box testing results.

System Feature	Expected Results	Actual Results
Welcome Screen	The system is able to display a welcome message in the beginning.	Valid
Process Selection Form	The user can choose a specific disease from the system.	Valid
Input Table	The user can input that will be further proceeded by the system.	Valid
Forecasting Results Sheet	The system is capable of displaying forecasting results in the selected sheet.	Valid
Result Charts	The system is able to illustrate result in the chart view.	Valid
ANOVA Results	The system is able to calculate ANOVA results and load this information.	Valid
Duncan Results	The system is capable of calculating Duncan method and views the results.	Valid
Coefficient of Variance Result	The system is able to compute Coefficient of Variance and display its results.	Valid

4.2.2. User evaluation testing

A questionnaire of User Interface Satisfaction from Chin [29] was adapted to evaluate the user interface. For evaluating the user interface, 4 questions in Screen part were given to the user. The answers were in 9 scales from 1-9. The question variables are described as follows:

- Reading characters on the screen (score: 1 = hard .... 9 = easy).
- Highlighting simplifies task (score: 1 = not all ..... 9 = very much)
- Organization of information (score: 1 = confusing ..... 9 = clear)
- Sequence of screens (score: 1 = confusing ..... 9 = clear)

The questionnaire was filled in accordance with the state of GUI screen. There were 4 respondents of the survey, 3 doctors and 1 medical staff who worked at the hospital. All respondents were experts and had a capability to evaluate the system. Therefore, the questionnaire results are summarized in Table 2.

Table 2. User evaluation results.

Variables	Average Score
Reading characters on the screen	6
Highlighting simplifies task	6.75
Organization of information	6.75
Sequence of screens	7.25

Table 2 shows the mean value of each survey component. Reading characters on the screen yields the smallest score (6) among all components. It is considered since in some screen the results are too small to be read. Whilst, highlighting simplifies task and organization of information score are 6.75. The highest score is obtained by the sequence of screens. This means screen flow can be followed by the reader. Results of Table 2 indicates that overall system screen is quite acceptable by users.

5. Conclusions

The user interface of zoonosis DSS presents the transformation for zoonosis prediction framework. The general zoonosis prediction framework has provided a systematic process forecasting a future number of seasonal zoonosis. The application of the proposed framework came out with GUI design that was a representation of three DSS components into a user-friendly interface. The user can access the system through this interface. The obtained result showed that the proposed system GUI can model zoonosis prediction system as proved by black box testing and user evaluation survey. The GUI design was provided as the interface connection between user and system.

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